IMPACT OF SHALL-ISSUE LAWS ON CRIME RATES

BUAN 6312- Spring 2018

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Contents

Abstract

In this document, we evaluate the shall-issue laws in the United States of America and study its effects on the rates of different types of crimes. The topic regarding the legal freedom to carry concealed weapons has been a controversial topic and has been debated on for several years. Proponents of the shall-issue law believe that this law serves as a way for citizens to defend themselves in life-threatening scenarios, whereas opponents believe that this law will result in an increase in crime rate due to shootings which would not take place if guns were not available.

For this project, we examine the effects of the shall-issue law over a period of 23 years (1977-1999) for 50 states plus the District of Columbia. We have tried various models to understand the trends in crime rates in the presence and absence of the shall-issue law. We have also taken into consideration factors such as income, population, young males, and ethnicity. Based on our findings, we conclude that the crime rates are not significantly affected by shall-issue laws (at 95% significance).

Data Description

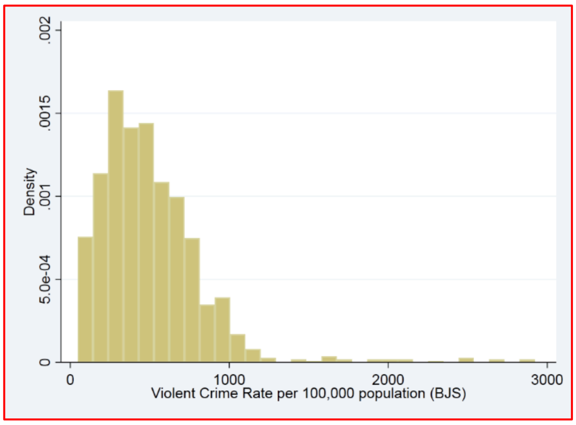
The data is in the form of panel data available for 50 US states, plus the District of Columbia, from year 1977 to 1999. It is a balanced panel and gives the rate of crimes for each state in a given year. We have violent crime rate, robbery rate and murder rate as the different types of crimes occurring per 100,000 members of the population. The variable 'shall' indicates the year in which the shall-issue law was present in that respective state. With this variable, we can divide the data in different groups and study the changes in crime rates in the presence and absence of the law.

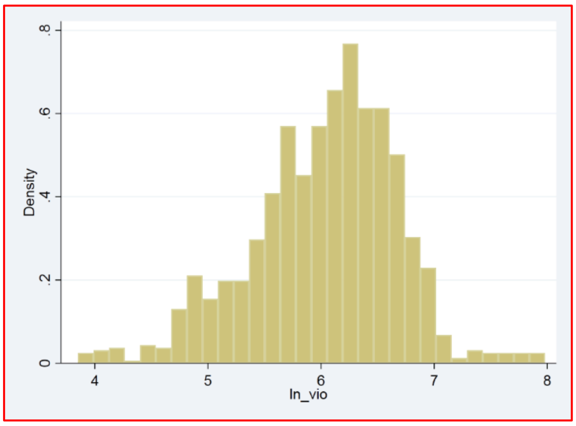
Incarceration rate gives us the number of sentenced prisoners per 100,000 residents in the previous year. This variable can have a simultaneous relation with the crime rates because as crime increases, incarceration rate will increase. However, it could also have been caused by a better trained police force which was more effective in catching perpetrators of crime. Data about the population of states in millions and population per square mile is also provided. We also have data of the percentage of state population that is white and black, and between the ages, 10 and 64.

Variable Analysis - Histograms

Vio: Violent Crime Rate (Incidents Per 100,000 Members Of The Population)

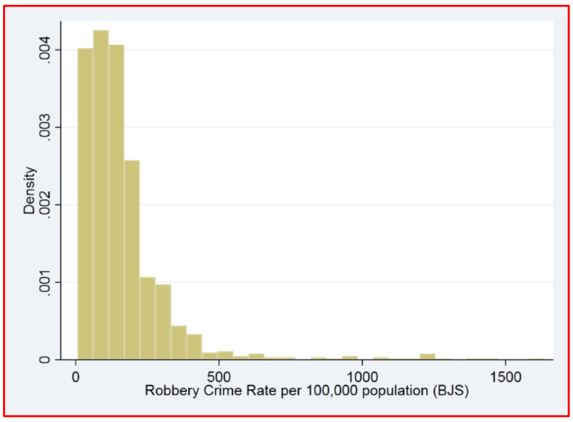
Shown below are the histograms of vio and ln_vio. Since vio is skewed, **we chose to use ln_vio.**

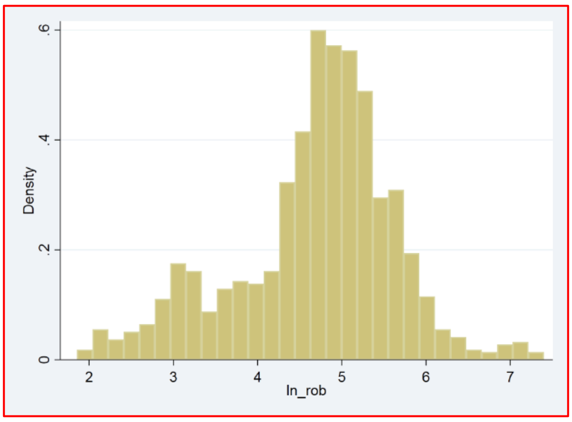




Rob: Robbery Rate (Incidents Per 100,000)

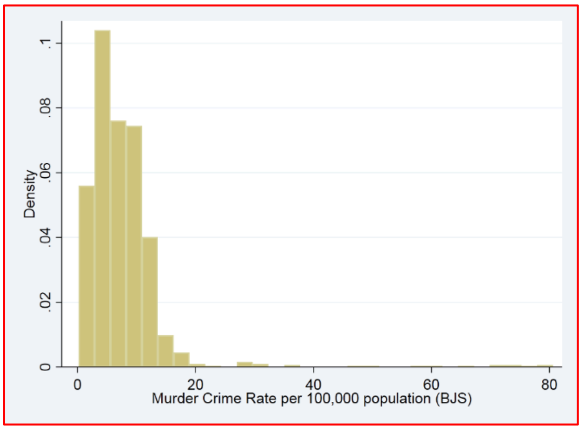
Shown below are the histograms of rob and ln_rob. Since rob is skewed, **we chose to use ln_rob.**

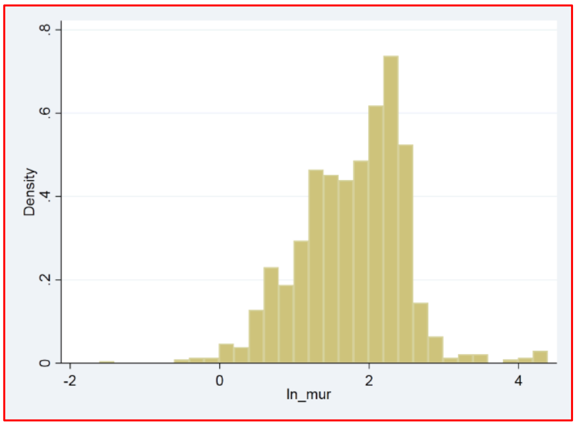




Mur: Murder Rate (Incidents Per 100,000)

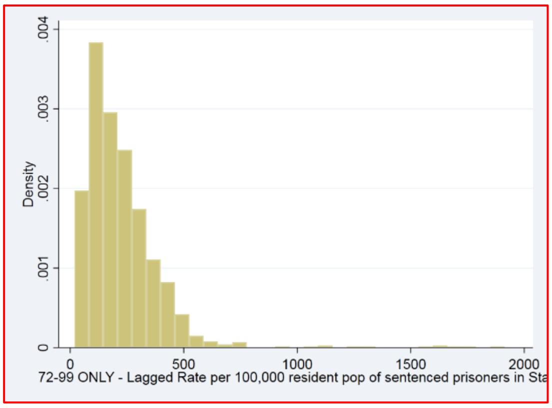
Shown below are the histograms of mur and ln_mur. Since mur is skewed, **we chose to use ln_mur.**

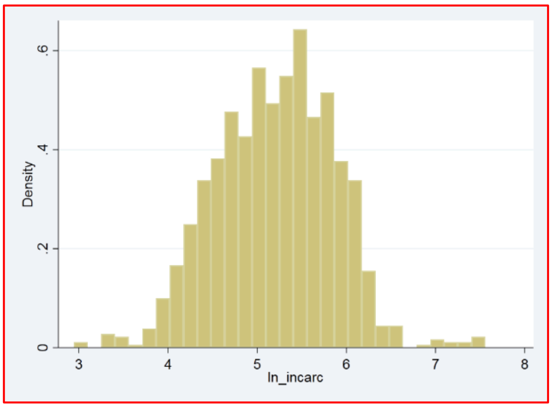




Incarc_Rate: Incarceration Rate In The State In The Previous Year (Sentenced Prisoners Per 100,000 Residents; Value For The Previous Year)

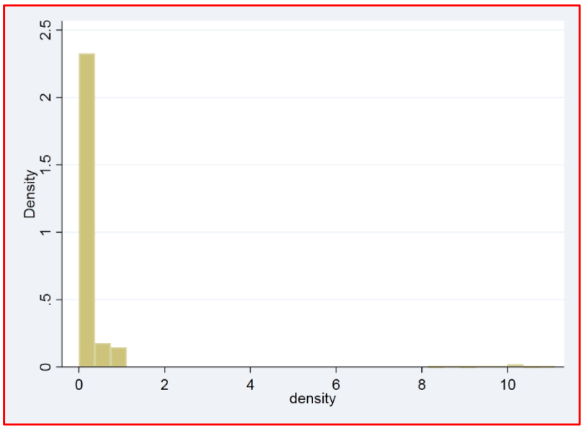
Shown below are the histograms of incarc_rate and ln_incarc_rate. Since incarc_rate is skewed, **we chose to use ln_incarc_rate.**

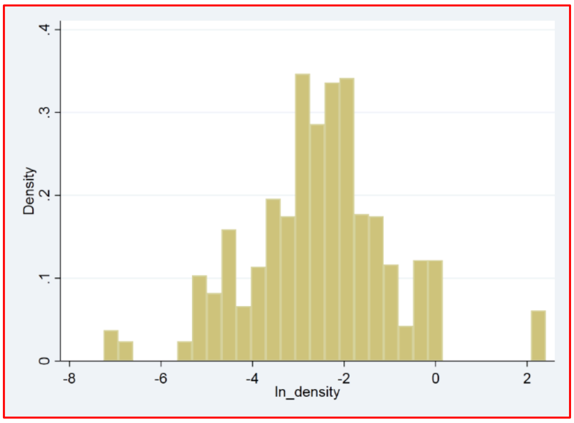




Density: Population Per Square Mile Of Land Area, Divided By 1000

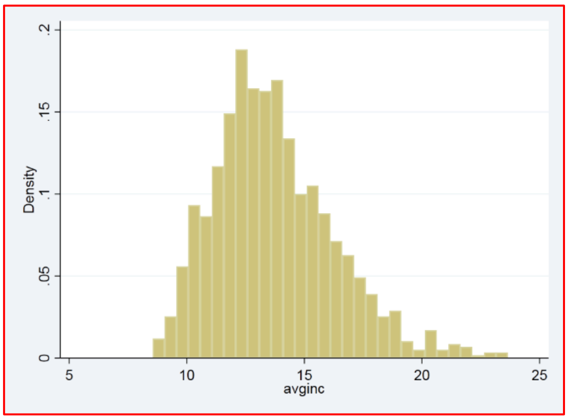
Shown below are the histograms of density and ln_density. Since density is skewed, **we chose to use ln_density.**

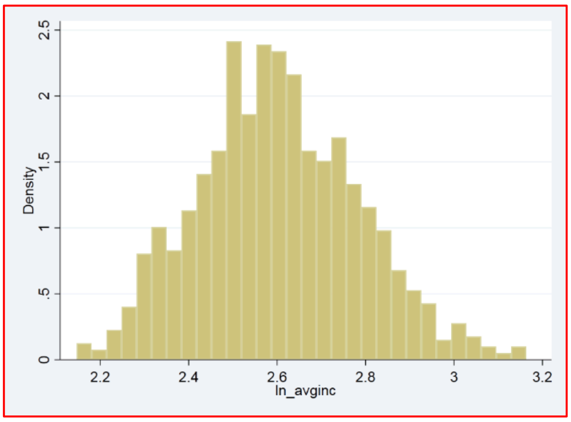




Avginc: Real Per Capita Personal Income In The State, In Thousands Of Dollars

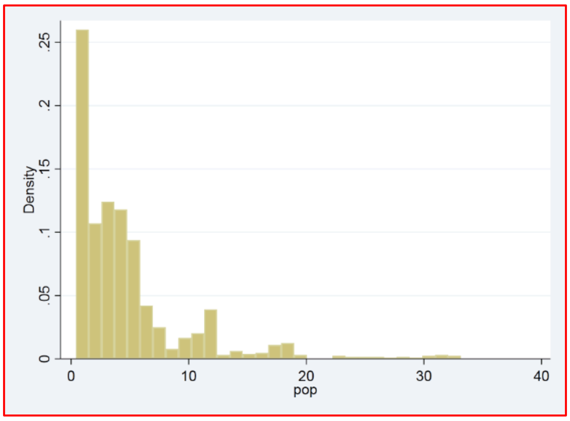
Shown below are the histograms of avginc and ln_avginc. Since avginc is not skewed, **we chose to use avginc.**

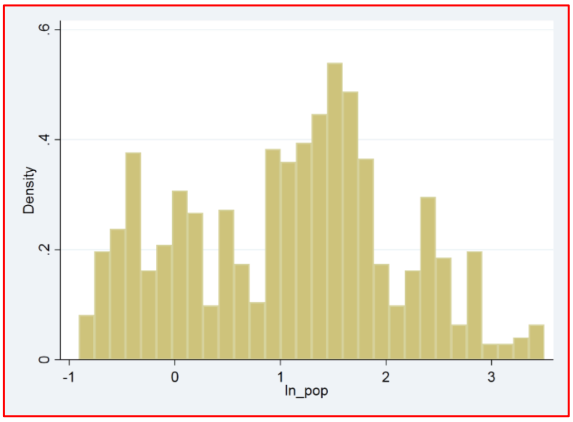




Pop: State Population, In Millions Of People

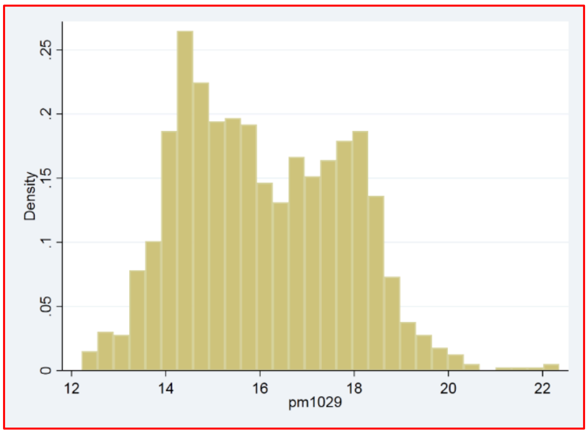
Shown below are the histograms of pop and ln_pop. Since pop is skewed, **we chose to use ln_pop.**

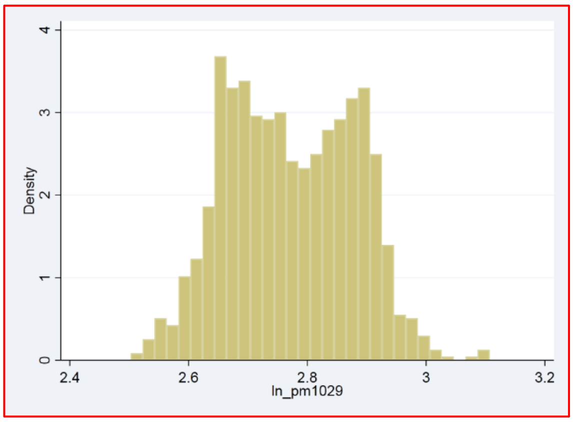




Pm1029: Percent Of State Population That Is Male, Ages 10 To 29

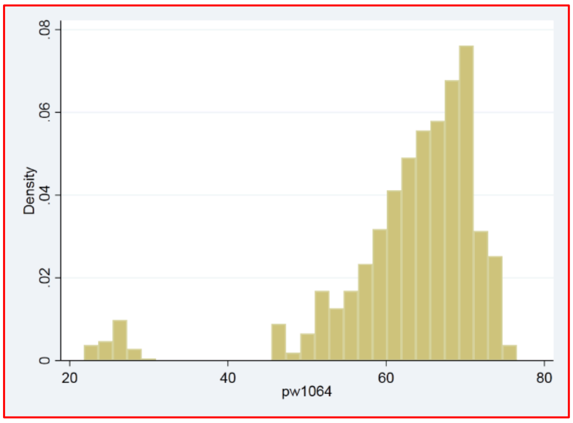
Shown below are the histograms of pm1029 and ln_pm1029. Since pm1029 is not skewed, **we chose to use pm1029.**

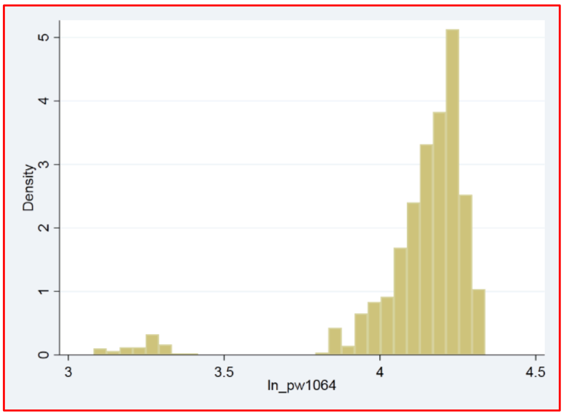




Pw1064: Percent Of State Population That Is White, Ages 10 To 64

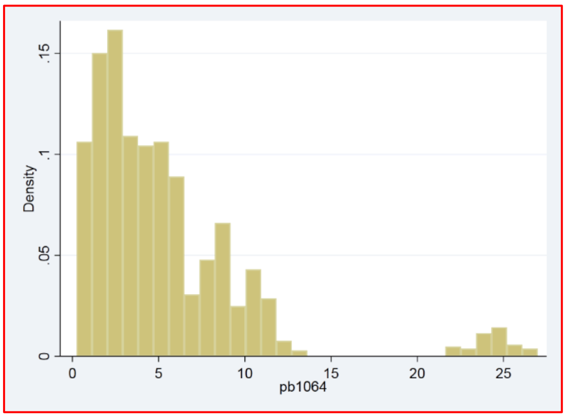
Shown below are the histograms of pw1064 and ln_pw1064. Since pw1064 is not skewed, **we chose to use pw1064**.

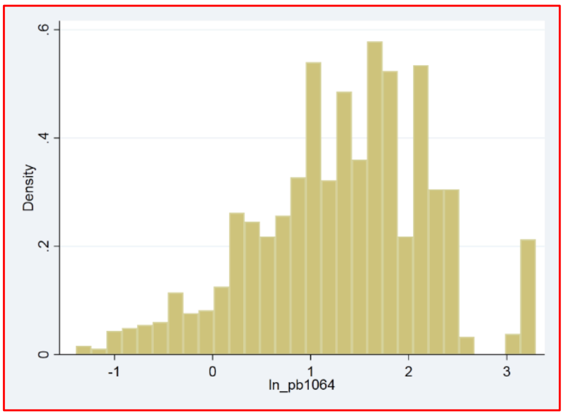




Pb1064: Percent Of State Population That Is Black, Ages 10 To 64

Shown below are the histograms of pb1064 and ln_pb1064. Even though pb1064 is a little skewed, **we chose to use pb1064** since we chose to use pw1064 and pm1029 instead of their lag transformations (for convenience purposes).



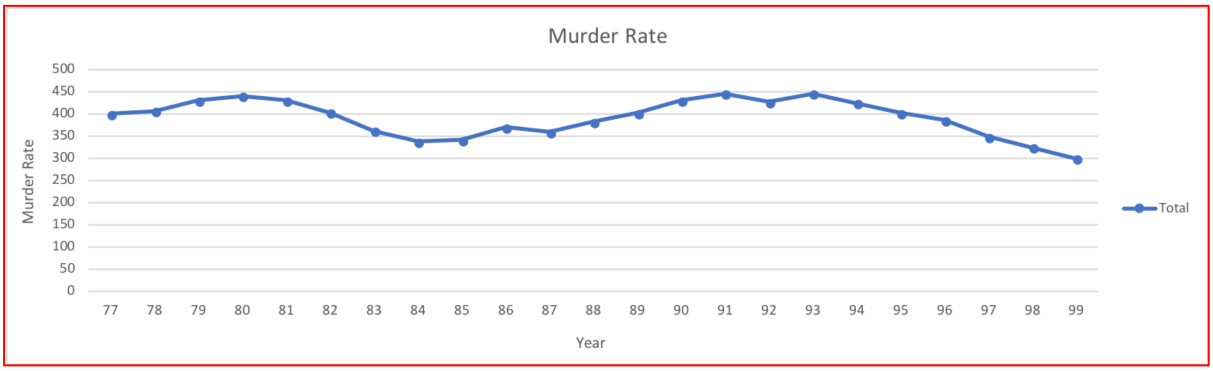


Overall Trend Analysis

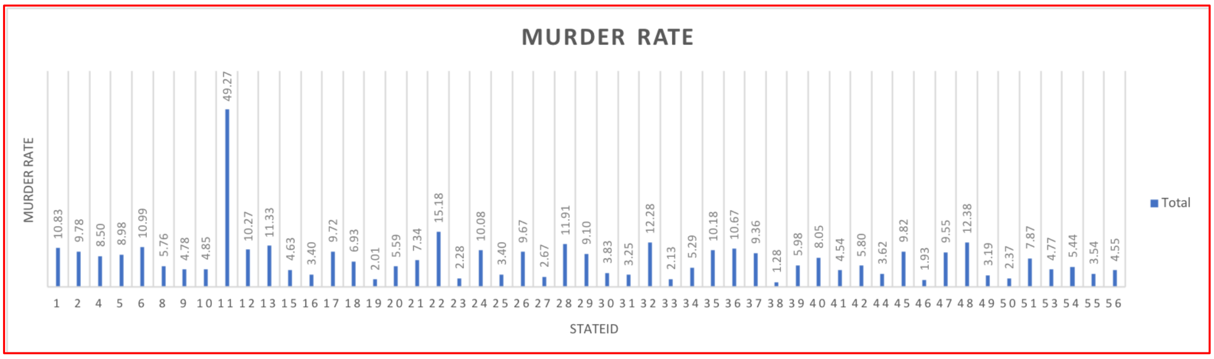
To better understand our data, we have plotted a few graphs to understand the relation between the different variables.

These plots show the trends of Murder rates, Robbery rates and Violent crime rates for all the states over all the years we have included in our dataset. State ID 11 (District of Columbia) has much higher crime rates for all types of crimes over the years. For all the years we have data, District of Columbia did not have the shall law implemented.

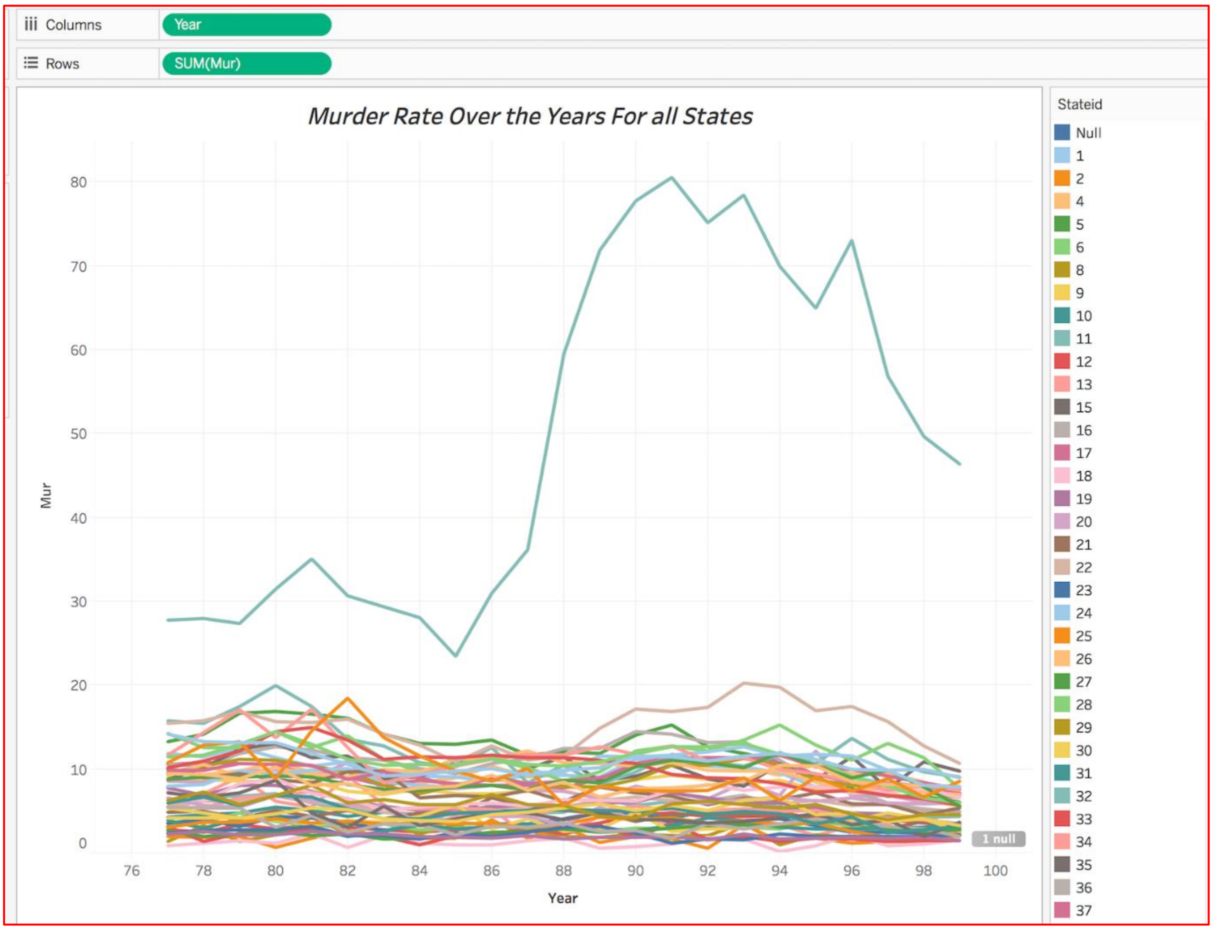
Murder Rate Over The Years



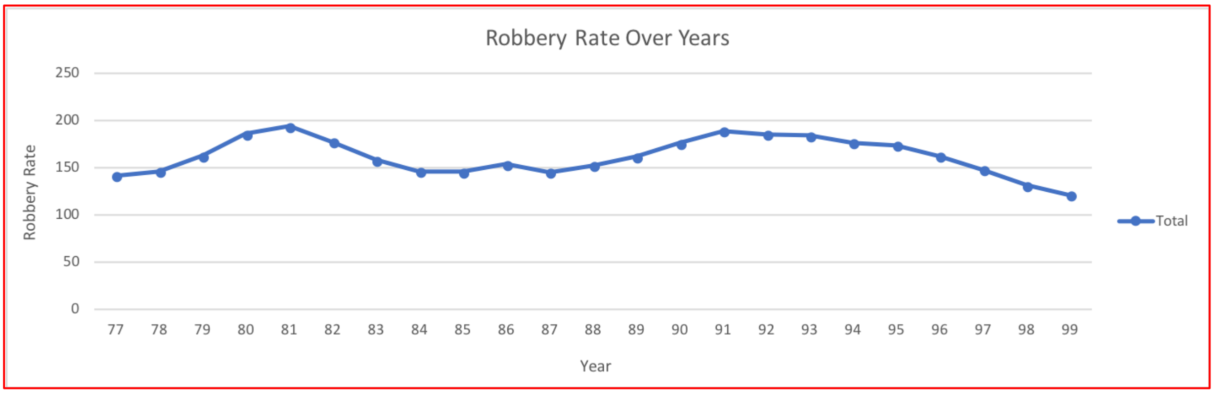
Murder Rate Over The Stateid



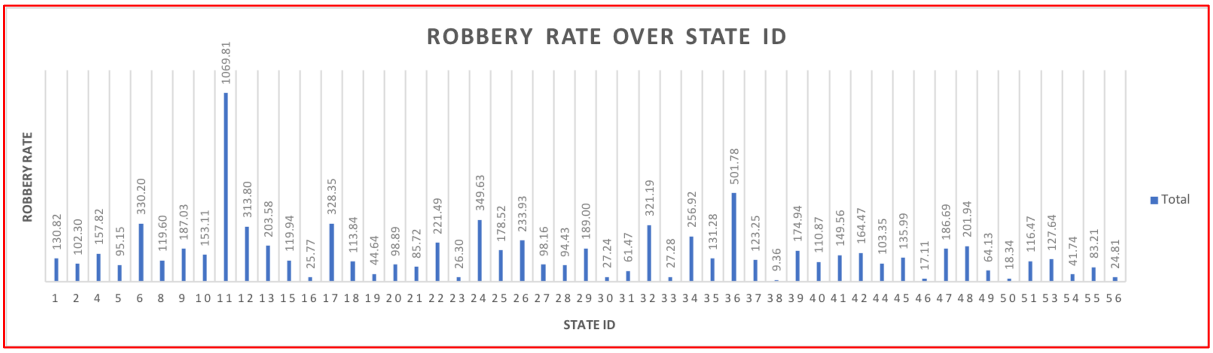
Murder Rate For All States



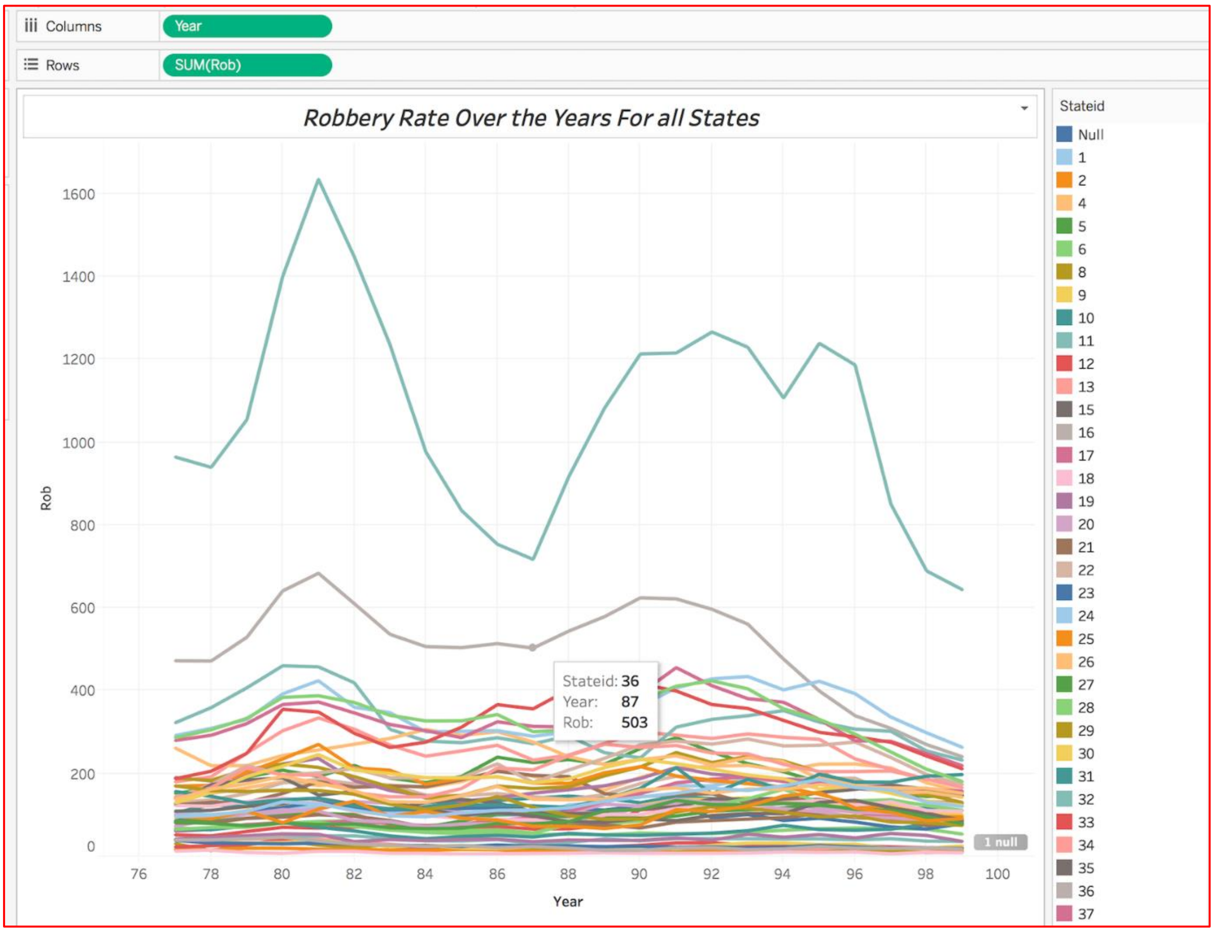
Robbery Rate Over The Years



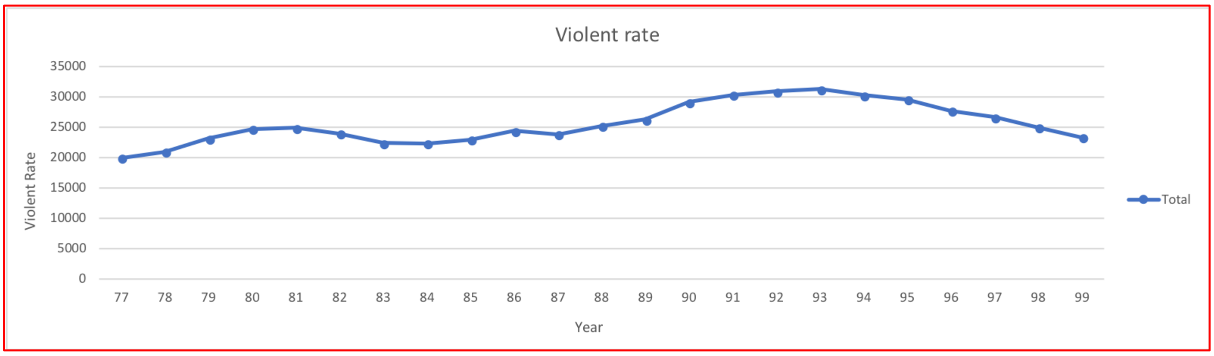
Robbery Rate Over The Stateid



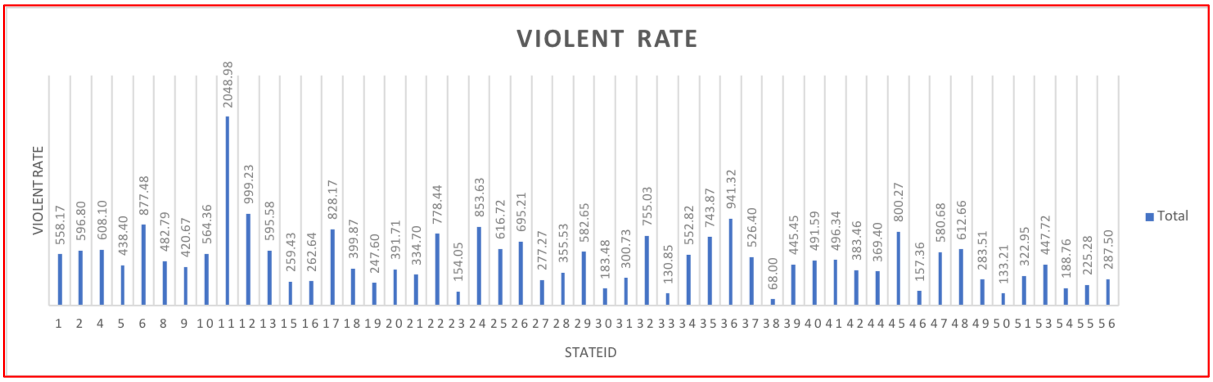
Robbery Rates For All States



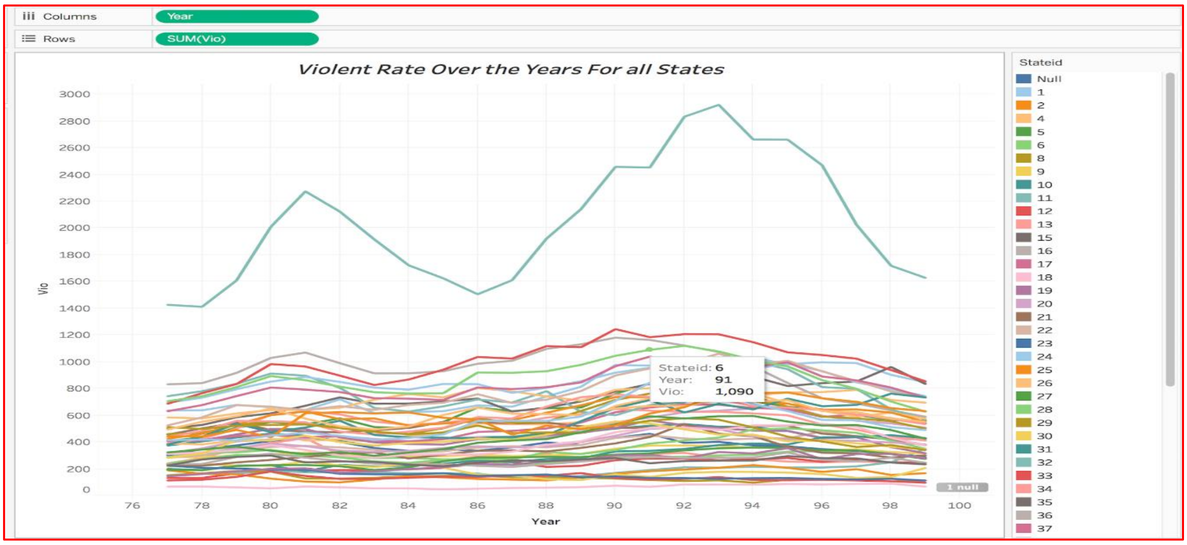
Violent Crime Rate Over The Years



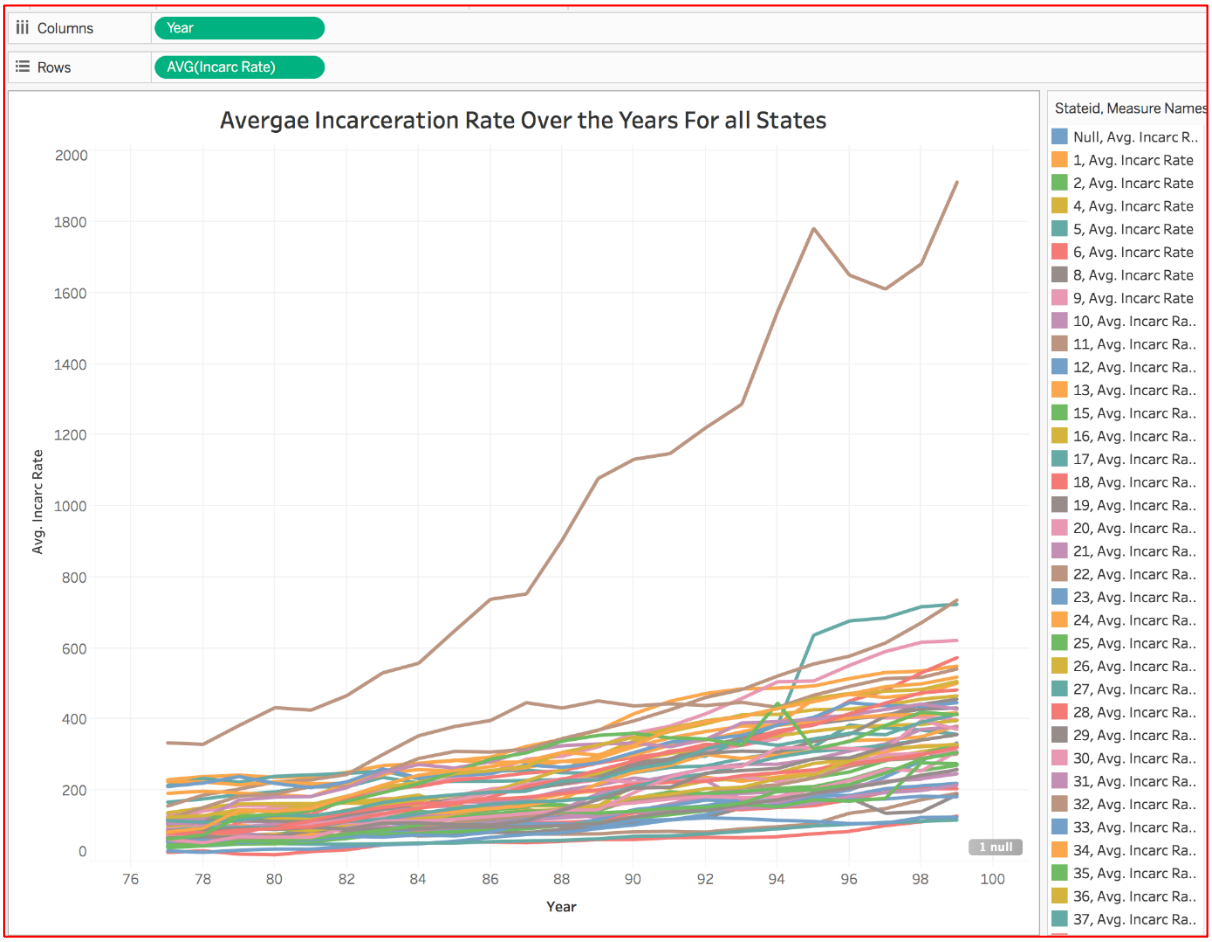
Violent Crime Rate Over Stateid



Violent Crime Rate For All States



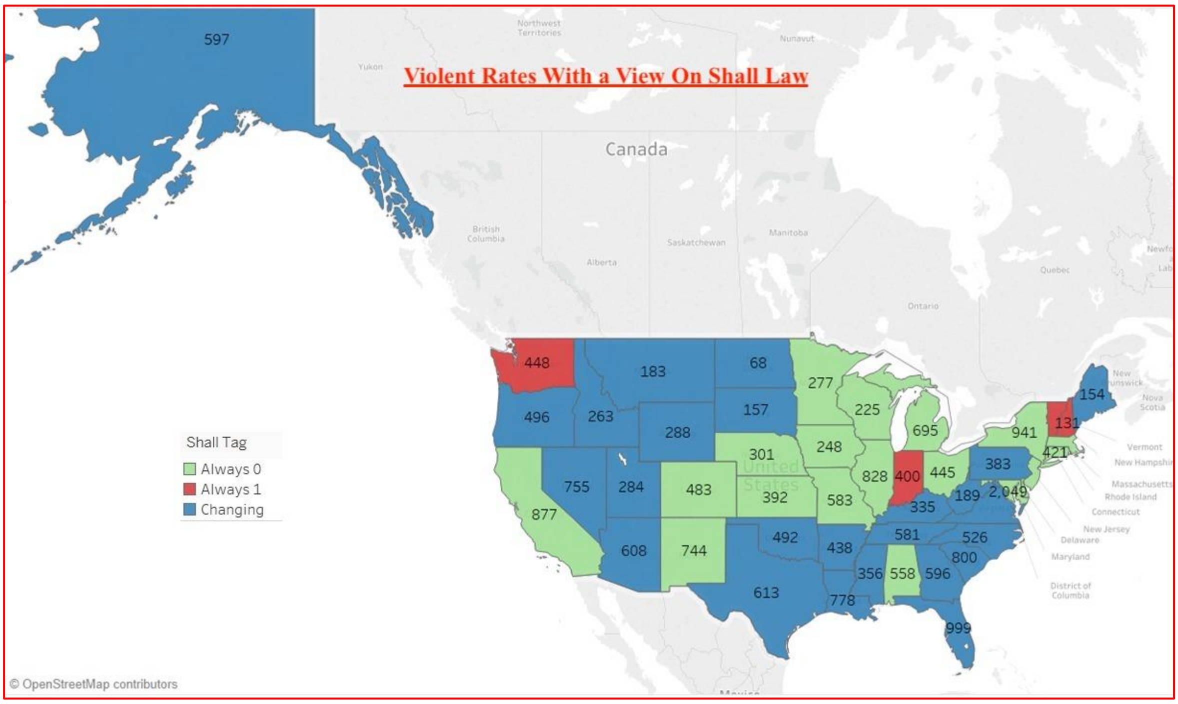
Average Incarceration Rate In All States



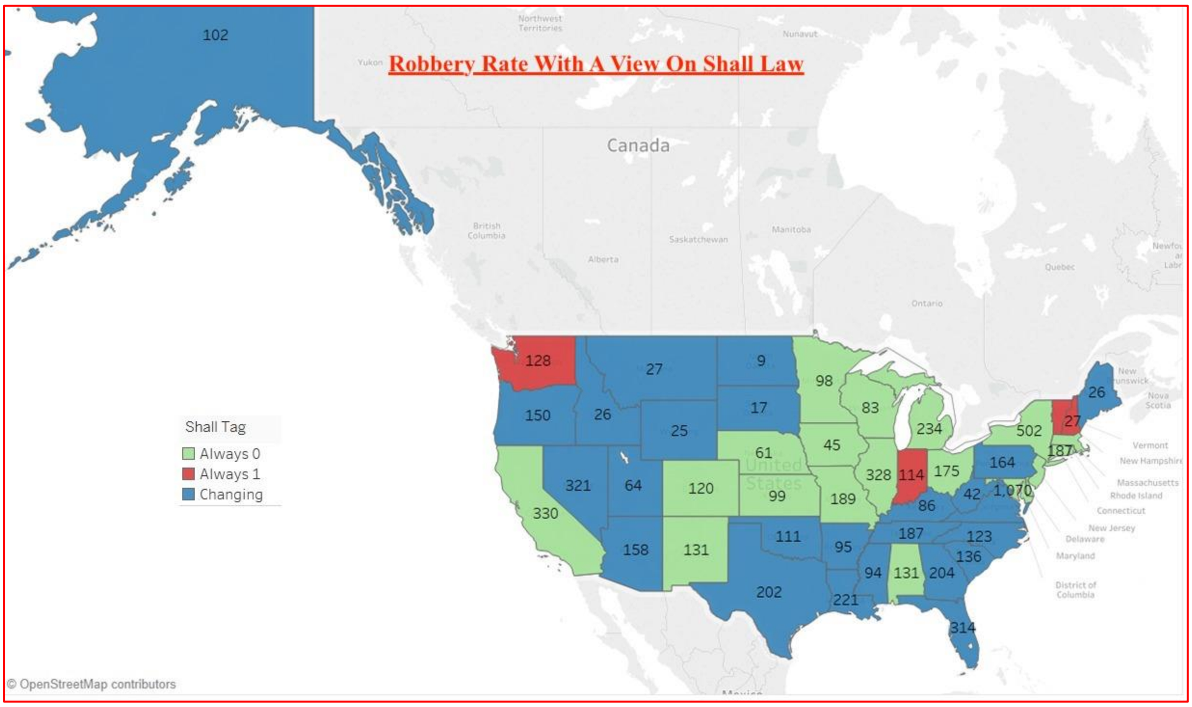
Heat Maps Analysis

After mapping stateIDs to State names within the USA, we plotted the crime rates for all the states using a heat map. Here, the difference in the rate for the various types of crimes are depicted.

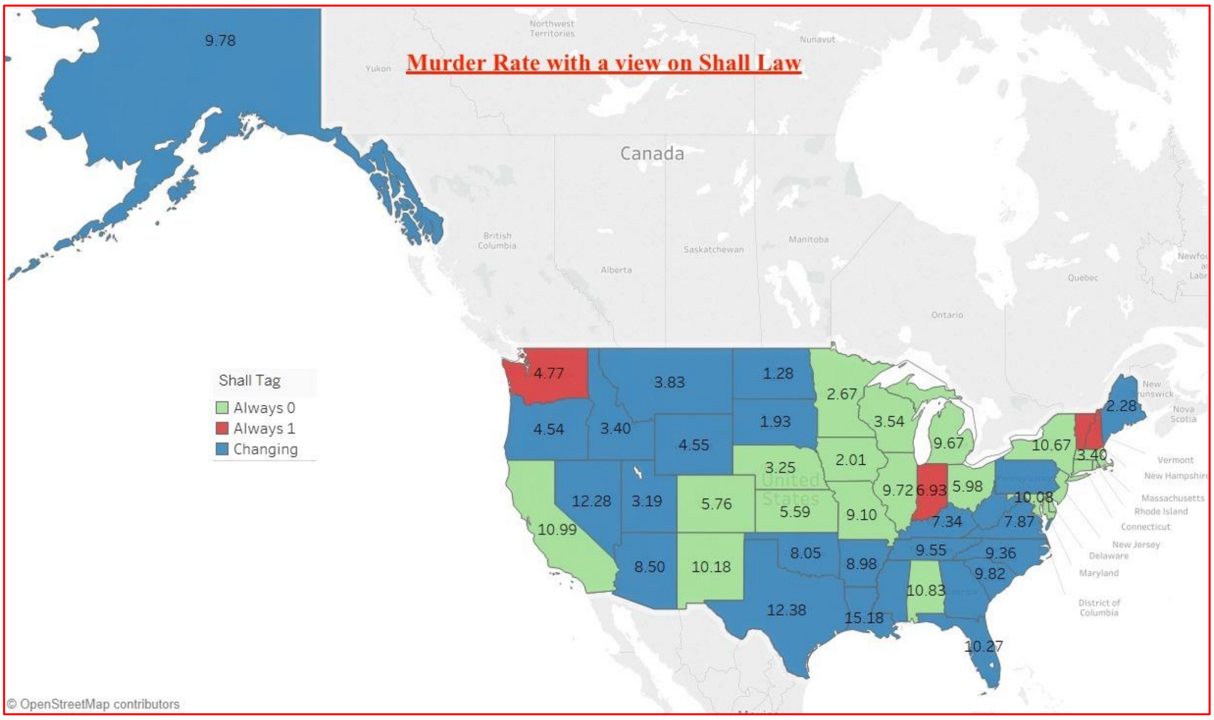
Violent Crime Rates In States With A View On Shall-Law



Robbery Rates In States With A View On Shall-Law



Murder Rates In States With A View On Shall-Law



Pearson's Correlation Matrix

We plot a correlation plot as a matrix to check the strength of correlation between the variables. All the types of crimes such as violent crime rate, murder rate and robbery are highly positively correlated. We observe that population density has moderate correlation crime rates as well as incarceration rates, implying that if the density of the population in a state is high, the crime rate can be assumed to be slighter higher than usual as well. Most other variables are insignificantly correlated.

Pearson's Correlation Matrix

	year	vio	mur	rob	incarc_rate	pb1064	pw1064	pm1029	pop	avginc	density	stateid	shall
year	1.00	0.12	-0.03	-0.01	0.50	0.07	-0.03	-0.87	0.06	0.53	0.00	0.00	0.38
vio	0.12	1.00	0.83	0.91	0.70	0.57	-0.57	-0.17	0.32	0.41	0.66	-0.32	-0.21
mur	-0.03	0.83	1.00	0.80	0.71	0.60	-0.62	0.01	0.10	0.22	0.75	-0.24	-0.18
rob	-0.01	0.91	0.80	1.00	0.57	0.58	-0.58	-0.09	0.32	0.41	0.78	-0.25	-0.21
incarc_rate	0.50	0.70	0.71	0.57	1.00	0.53	-0.53	-0.45	0.10	0.46	0.56	-0.22	0.04
pb1064	0.07	0.57	0.60	0.58	0.53	1.00	-0.98	0.02	0.06	0.26	0.54	-0.31	-0.18
pw1064	-0.03	-0.57	-0.62	-0.58	-0.53	-0.98	1.00	-0.01	-0.07	-0.19	-0.56	0.31	0.21
pm1029	-0.87	-0.17	0.01	-0.09	-0.45	0.02	-0.01	1.00	-0.10	-0.53	-0.06	0.01	-0.28
pop	0.06	0.32	0.10	0.32	0.10	0.06	-0.07	-0.10	1.00	0.22	-0.08	-0.06	-0.12
avginc	0.53	0.41	0.22	0.41	0.46	0.26	-0.19	-0.53	0.22	1.00	0.34	-0.20	0.00
density	0.00	0.66	0.75	0.78	0.56	0.54	-0.56	-0.06	-0.08	0.34	1.00	-0.16	-0.11
stateid	0.00	-0.32	-0.24	-0.25	-0.22	-0.31	0.31	0.01	-0.06	-0.20	-0.16	1.00	0.19
shall	0.38	-0.21	-0.18	-0.21	0.04	-0.18	0.21	-0.28	-0.12	0.00	-0.11	0.19	1.00

Pb1064 and pw1064 are very highly correlated (correlation of 0.98. This makes sense because pb1064 is percentage of black people and pw1064 is the percentage of white people (The higher the number of black people, the lower the number of white people).

Thus, for our regression analysis, we will eliminate pw1064 and keep only pb1064.

Regression Models

We have run several models and considered each of the variables as a dependent variable to get a conclusion on which model best describes our data set.

Violent Crime Rate

Pooled OLS Model

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

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.162946 -0.217904  0.014964  0.245733  1.127465

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)       0.0917191  0.2578168  0.3558    0.7221
shall            -0.2520324  0.0268825 -9.3753 < 2.2e-16 ***
log(incarc_rate)  0.6624393  0.0247900 26.7220 < 2.2e-16 ***
log(density)      0.0648197  0.0091694  7.0691 2.680e-12 ***
avginc            0.0379865  0.0053061  7.1590 1.436e-12 ***
log(pop)          0.1653451  0.0122286 13.5212 < 2.2e-16 ***
pb1064            0.0014807  0.0031377  0.4719    0.6371
pm1029            0.1248594  0.0093749 13.3185 < 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: 151.9
R-Squared:      0.68913
Adj. R-Squared: 0.68727
F-statistic: 368.941 on 7 and 1165 DF, p-value: < 2.22e-16
```

Fixed Effect Model

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

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

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.50711821 -0.09749124  0.00094333  0.10157345  0.56833378

Coefficients:
                     Estimate Std. Error t-value  Pr(>|t|)
shall              -0.0343896  0.0183496 -1.8741   0.06117 .
log(incarc_rate)   -0.0020986  0.0269383 -0.0779   0.93792
log(density)        2.3124147  1.4756173  1.5671   0.11738
avginc              0.2134522  0.0231451  9.2223 < 2.2e-16 ***
I(avginc * avginc) -0.0067803  0.0007086 -9.5685 < 2.2e-16 ***
log(pop)           -2.5951128  1.4615538 -1.7756   0.07607 .
pb1064              0.0156754  0.0120219  1.3039   0.19254
pm1029             -0.0396117  0.0080010 -4.9509  8.53e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.031
R-Squared:      0.23807
Adj. R-Squared: 0.1984
F-statistic: 43.5102 on 8 and 1114 DF, p-value: < 2.22e-16
```

Entity-Time Fixed Model

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

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall            -0.0280351  0.0173538 -1.6155 0.1064919
factor(year)78    0.0666510  0.0278251  2.3954 0.0167718 *
factor(year)79    0.1848990  0.0281916  6.5587 8.359e-11 ***
factor(year)80    0.2470589  0.0284627  8.6801 < 2.2e-16 ***
factor(year)81    0.2548344  0.0290910  8.7599 < 2.2e-16 ***
factor(year)82    0.2476727  0.0307305  8.0595 1.995e-15 ***
factor(year)83    0.2254772  0.0330875  6.8146 1.559e-11 ***
factor(year)84    0.2667165  0.0359294  7.4233 2.292e-13 ***
factor(year)85    0.3246295  0.0388135  8.3638 < 2.2e-16 ***
factor(year)86    0.4120452  0.0424057  9.7168 < 2.2e-16 ***
factor(year)87    0.4203359  0.0459122  9.1552 < 2.2e-16 ***
factor(year)88    0.4912605  0.0496277  9.8989 < 2.2e-16 ***
factor(year)89    0.5556994  0.0531668 10.4520 < 2.2e-16 ***
factor(year)90    0.6900469  0.0563632 12.2429 < 2.2e-16 ***
factor(year)91    0.7541239  0.0591846 12.7419 < 2.2e-16 ***
factor(year)92    0.7961578  0.0624772 12.7432 < 2.2e-16 ***
factor(year)93    0.8277776  0.0647324 12.7877 < 2.2e-16 ***
factor(year)94    0.8232347  0.0673599 12.2214 < 2.2e-16 ***
factor(year)95    0.8284021  0.0702121 11.7986 < 2.2e-16 ***
factor(year)96    0.7833969  0.0730443 10.7250 < 2.2e-16 ***
factor(year)97    0.7718966  0.0756353 10.2055 < 2.2e-16 ***
factor(year)98    0.7257012  0.0784862  9.2462 < 2.2e-16 ***
factor(year)99    0.6753965  0.0806172  8.3778 < 2.2e-16 ***
log(incarc_rate) -0.1003786  0.0279386 -3.5928 0.0003417 ***
log(density)     -0.6839064  1.3151138 -0.5200 0.6031439
avginc            0.0027434  0.0061904  0.4432 0.6577371
log(pop)          0.4545895  1.3026007  0.3490 0.7271670
pb1064           -0.0071716  0.0109824 -0.6530 0.5138896
pm1029            0.0773402  0.0112926  6.8488 1.241e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.143
R-Squared:      0.4253
Adj. R-Squared: 0.38376
```

Comparing between FE and Time FE

```
> pFtest(Vio_Time_FE, Vio_FE) # Test to find determine difference between states based on individual and time fixed effects

        F test for individual effects

data:  log(vio) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
F = 16.956, df1 = 21, df2 = 1093, p-value < 2.2e-16
alternative hypothesis: significant effects
```

As seen in the screenshot above, the combined effect of the time variables is significant. Thus, we accept the Time FE model over the FE model.

Random Effect Model

```
> Vio_RE <- plm(log(vio) ~ shall + factor(year) + log(incarc_rate) + log(density) + avginc +
+                          log(pop) + pb1064 + pm1029, index=c("stateid","year"), model = "random", data = Data)
> phtest(Vio_Time_FE, Vio_RE)

        Hausman Test

data:  log(vio) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
chisq = 35.029, df = 29, p-value = 0.2036
alternative hypothesis: one model is inconsistent
```

We do not reject the Null Hypothesis and conclude that the RE model does not have endogeneity. Therefore, we accept the RE model since the RE model is more efficient than FE.

Here, we know that Random Effect Model is used usually when we our entities are randomly chosen, which is not true for our dataset. However, we still choose the RE Model because the Hausman Test shows that there is no endogeneity in this model. Since RE is more efficient than the FE model, we go with this model for the violent crime rate.

```
Coefficients:
                    Estimate Std. Error t-value  Pr(>|t|)
(Intercept)        4.1693514  0.2804216 14.8682 < 2.2e-16 ***
shall             -0.0338972  0.0181560 -1.8670  0.062157 .
factor(year)78     0.0515048  0.0296761  1.7356  0.082910 .
factor(year)79     0.1549115  0.0299580  5.1710 2.748e-07 ***
factor(year)80     0.2094482  0.0301862  6.9386 6.621e-12 ***
factor(year)81     0.2070954  0.0307203  6.7413 2.485e-11 ***
factor(year)82     0.1818867  0.0321747  5.6531 1.989e-08 ***
factor(year)83     0.1401172  0.0342841  4.0869 4.676e-05 ***
factor(year)84     0.1649935  0.0368418  4.4784 8.273e-06 ***
factor(year)85     0.2103088  0.0395267  5.3207 1.243e-07 ***
factor(year)86     0.2835861  0.0429024  6.6100 5.882e-11 ***
factor(year)87     0.2789706  0.0462241  6.0352 2.143e-09 ***
factor(year)88     0.3362941  0.0497337  6.7619 2.168e-11 ***
factor(year)89     0.3866041  0.0530584  7.2864 5.922e-13 ***
factor(year)90     0.5021461  0.0564924  8.8887 < 2.2e-16 ***
factor(year)91     0.5551608  0.0592354  9.3721 < 2.2e-16 ***
factor(year)92     0.5818420  0.0622949  9.3401 < 2.2e-16 ***
factor(year)93     0.6015370  0.0643920  9.3418 < 2.2e-16 ***
factor(year)94     0.5838613  0.0668262  8.7370 < 2.2e-16 ***
factor(year)95     0.5747210  0.0694667  8.2733 3.593e-16 ***
factor(year)96     0.5160220  0.0720707  7.1599 1.441e-12 ***
factor(year)97     0.4908696  0.0743959  6.5981 6.357e-11 ***
factor(year)98     0.4278942  0.0768825  5.5656 3.254e-08 ***
factor(year)99     0.3642801  0.0787252  4.6272 4.129e-06 ***
log(incarc_rate)   0.0112401  0.0279847  0.4017  0.688016
log(density)       0.0616500  0.0325531  1.8938  0.058500 .
avginc             0.0110842  0.0061940  1.7895  0.073798 .
log(pop)           0.1124813  0.0425533  2.6433  0.008322 **
pb1064             0.0243561  0.0076116  3.1999  0.001413 **
pm1029             0.0759918  0.0116509  6.5224 1.037e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    41.486
Residual Sum of Squares: 25.257
R-Squared:      0.39119
```

Interpretation of Selected Model: Random Effect Model

According to the Random Effect Model, we see that having the shall-issue law decreases violent crimes rates by 3.38%. However, this is not significant even at a 95% confidence level. Thus, we cannot make any statistically significant conclusion about the effect of shall-issue laws on violent crimes rates.

The effect of percentage of incarceration rate is statistically insignificant at a 90% confidence level. The effect of percentage of density and average income is statistically insignificant at a 95% confidence level.

Having a unit percent increase in males between 10-29 (having a unit increase in pm1029) increases the violent crimes rates by 7.60% and is significant at a 99% confidence level.

An increase in population by 1% results in an increase of 0.11% in the violent crimes rate. One unit increase in the percentage of black people between the age of 10 to 64 increase the violent crimes rate by 2.43%.

Murder Rate

Pooled OLS Model

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

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.050885 -0.252925  0.021335  0.266389  1.224744

Coefficients:
                   Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)      -4.5287955  0.2932117 -15.4455 < 2.2e-16 ***
shall            -0.1847276  0.0305731  -6.0422 2.043e-09 ***
log(incarc_rate)  0.7092860  0.0281934  25.1579 < 2.2e-16 ***
log(density)      0.0486992  0.0104282   4.6699 3.363e-06 ***
avginc           -0.0262214  0.0060346  -4.3452 1.513e-05 ***
log(pop)          0.1537004  0.0139074  11.0517 < 2.2e-16 ***
pb1064            0.0289677  0.0035685   8.1177 1.199e-15 ***
pm1029            0.1759592  0.0106619  16.5035 < 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: 196.47
R-Squared:      0.6612
Adj. R-Squared: 0.65917
F-statistic: 324.803 on 7 and 1165 DF, p-value: < 2.22e-16
```

Fixed Effect Model

```
plm(formula = log(mur) ~ shall + log(incarc_rate) + log(density) +
    avginc + I(avginc * avginc) + log(pop) + pb1064 + pm1029,
    data = Data, model = "within", index = c("stateid", "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.7116575 -0.1203881  0.0015791  0.1280763  0.8418951

Coefficients:
                      Estimate  Std. Error t-value  Pr(>|t|)
shall              -0.04927332  0.02532130 -1.9459  0.051915 .
log(incarc_rate)   -0.14915442  0.03717310 -4.0124 6.411e-05 ***
log(density)        8.94242848  2.03625479  4.3916 1.232e-05 ***
avginc              0.06528417  0.03193874  2.0440  0.041184 *
I(avginc * avginc) -0.00098869  0.00097782 -1.0111  0.312179
log(pop)           -9.29651356  2.01684801 -4.6094 4.504e-06 ***
pb1064             -0.05150683  0.01658950 -3.1048  0.001952 **
pm1029              0.01379667  0.01104082  1.2496  0.211706
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 53.376
R-Squared:      0.15696
Adj. R-Squared: 0.11307
F-statistic: 25.926 on 8 and 1114 DF, p-value: < 2.22e-16
```

Entity- Time Fixed Model

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

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall            -0.0297496  0.0254937 -1.1669 0.2434891
factor(year)78    0.0074721  0.0408766  0.1828 0.8549912
factor(year)79    0.0823994  0.0414149  1.9896 0.0468830 *
factor(year)80    0.1266697  0.0418133  3.0294 0.0025078 **
factor(year)81    0.1445862  0.0427363  3.3832 0.0007418 ***
factor(year)82    0.0804880  0.0451448  1.7829 0.0748827 .
factor(year)83    0.0384306  0.0486073  0.7906 0.4293291
factor(year)84   -0.0621754  0.0527822 -1.1780 0.2390688
factor(year)85   -0.0087072  0.0570191 -0.1527 0.8786577
factor(year)86    0.0713869  0.0622962  1.1459 0.2520761
factor(year)87    0.0609952  0.0674475  0.9043 0.3660162
factor(year)88    0.0796925  0.0729057  1.0931 0.2745952
factor(year)89    0.0902049  0.0781048  1.1549 0.2483750
factor(year)90    0.1646234  0.0828006  1.9882 0.0470395 *
factor(year)91    0.2215505  0.0869453  2.5482 0.0109652 *
factor(year)92    0.1941665  0.0917824  2.1155 0.0346122 *
factor(year)93    0.2891296  0.0950954  3.0404 0.0024188 **
factor(year)94    0.1863232  0.0989552  1.8829 0.0599788 .
factor(year)95    0.2093374  0.1031453  2.0295 0.0426453 *
factor(year)96    0.1500898  0.1073059  1.3987 0.1621837
factor(year)97    0.0531337  0.1111123  0.4782 0.6326048
factor(year)98   -0.0030633  0.1153004 -0.0266 0.9788093
factor(year)99   -0.0651276  0.1184309 -0.5499 0.5824860
log(incarc_rate) -0.1123854  0.0410433 -2.7382 0.0062777 **
log(density)      6.1420496  1.9319726  3.1792 0.0015185 **
avginc            0.0611497  0.0090941  6.7241 2.841e-11 ***
log(pop)         -6.4219119  1.9135900 -3.3559 0.0008181 ***
pb1064           -0.0554886  0.0161338 -3.4393 0.0006053 ***
pm1029            0.0636071  0.0165894  3.8342 0.0001332 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 45.628
R-Squared:      0.27933
Adj. R-Squared: 0.22724
```

Comparing between FE and Time FE

```
> pFtest(Mur_Time_FE, Mur_FE)

        F test for individual effects

data:  log(mur) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
F = 8.8377, df1 = 21, df2 = 1093, p-value < 2.2e-16
alternative hypothesis: significant effects
```

As seen in the screenshot above, the combined effect of the time variables is significant. Thus, we accept the Time FE model over the FE model.

Random Effect Model

```
> Mur_RE <- plm(log(mur) ~ shall + factor(year) + log(incarc_rate) + log(density) + avginc +
+                    log(pop) + pb1064 + pm1029, index=c("stateid","year"),model = "random", data = Data)
> phtest(Mur_RE, Mur_Time_FE)

        Hausman Test

data:  log(mur) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
chisq = 400.7, df = 29, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

We reject the Null Hypothesis and observe that the RE model has endogeneity. Therefore, we reject the RE model.

Interpretation of Selected Model: Entity-Time Fixed Model

According to the Entity-Time Fixed Model, we see that having the shall-issue law decreases murder rates by 2.97%. However, this is not significant even at a 90% confidence level. Thus, we cannot make any statistically significant conclusion about the effect of shall-issue laws on murder rates.

Increasing the incarceration rate by 1% reduces the murder rates by 0.112% and is significant at a 99% confidence level. Having a unit percent increase in males between 10-29 (having a unit increase in pm1029) increases the murder rates by 6.36% and is significant at a 99% confidence level.

An increase in density by 1% results in an increase of 6.14% in the murder rate. An increase in average income by 1,000$ results in an increase of 6.11% in the murder rate. An increase in population by 1% results in a decrease of 6.42% in the murder rate. One unit increase in the percentage of black people between the age of 10 to 64 decreases the murder rate by 5.54%.

Robbery Rate

Pooled OLS Model

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

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.4104250 -0.3088917 -0.0024348  0.3151996  1.7244228

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)      -2.1065074  0.3469016 -6.0723 1.704e-09 ***
shall            -0.3382273  0.0361713 -9.3507 < 2.2e-16 ***
log(incarc_rate)  0.5349562  0.0333558 16.0379 < 2.2e-16 ***
log(density)      0.1602395  0.0123377 12.9878 < 2.2e-16 ***
avginc            0.0817516  0.0071396 11.4505 < 2.2e-16 ***
log(pop)          0.3624161  0.0164540 22.0261 < 2.2e-16 ***
pb1064            0.0250461  0.0042219  5.9324 3.931e-09 ***
pm1029            0.1773697  0.0126142 14.0611 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1068
Residual Sum of Squares: 275.01
R-Squared:      0.74251
Adj. R-Squared: 0.74096
F-statistic: 479.92 on 7 and 1165 DF, p-value: < 2.22e-16
```

Fixed Effect Model

```
plm(formula = log(rob) ~ shall + log(incarc_rate) + log(density) +
    avginc + I(avginc * avginc) + log(pop) + pb1064 + pm1029,
    data = Data, model = "within", index = c("stateid", "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.6691728 -0.1357107 -0.0005526  0.1359128  0.9035196

Coefficients:
                      Estimate  Std. Error t-value  Pr(>|t|)
shall              -0.03296933  0.02396788 -1.3756   0.16923
log(incarc_rate)   -0.14764522  0.03518620 -4.1961 2.931e-05 ***
log(density)        9.78519933  1.92741702  5.0768 4.495e-07 ***
avginc              0.25235725  0.03023162  8.3475 < 2.2e-16 ***
I(avginc * avginc) -0.00813093  0.00092556 -8.7849 < 2.2e-16 ***
log(pop)           -9.70336961  1.90904753 -5.0828 4.358e-07 ***
pb1064              0.03882640  0.01570279  2.4726   0.01356 *
pm1029              0.00537699  0.01045069  0.5145   0.60700
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 47.823
R-Squared:      0.10655
Adj. R-Squared: 0.060033
F-statistic: 16.6065 on 8 and 1114 DF, p-value: < 2.22e-16
```

Entity- Time Fixed Model

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

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall            -0.0028195  0.0237508 -0.1187 0.9055265
factor(year)78    0.0367847  0.0380821  0.9659 0.3342924
factor(year)79    0.1554782  0.0385836  4.0296 5.973e-05 ***
factor(year)80    0.2635845  0.0389547  6.7664 2.148e-11 ***
factor(year)81    0.2986557  0.0398146  7.5012 1.306e-13 ***
factor(year)82    0.2645872  0.0420585  6.2909 4.557e-10 ***
factor(year)83    0.1917425  0.0452843  4.2342 2.486e-05 ***
factor(year)84    0.1582200  0.0491738  3.2176 0.0013308 **
factor(year)85    0.2007764  0.0531210  3.7796 0.0001656 ***
factor(year)86    0.2903997  0.0580373  5.0037 6.551e-07 ***
factor(year)87    0.2694566  0.0628365  4.2882 1.960e-05 ***
factor(year)88    0.3148652  0.0679215  4.6357 3.986e-06 ***
factor(year)89    0.3815073  0.0727652  5.2430 1.896e-07 ***
factor(year)90    0.4732430  0.0771399  6.1349 1.190e-09 ***
factor(year)91    0.6016554  0.0810013  7.4277 2.220e-13 ***
factor(year)92    0.6082494  0.0855077  7.1134 2.044e-12 ***
factor(year)93    0.6319515  0.0885942  7.1331 1.783e-12 ***
factor(year)94    0.6536661  0.0921902  7.0904 2.396e-12 ***
factor(year)95    0.6679467  0.0960938  6.9510 6.226e-12 ***
factor(year)96    0.6214403  0.0999700  6.2163 7.231e-10 ***
factor(year)97    0.5625232  0.1035161  5.4342 6.786e-08 ***
factor(year)98    0.4751227  0.1074179  4.4231 1.070e-05 ***
factor(year)99    0.4040271  0.1103344  3.6618 0.0002624 ***
log(incarc_rate) -0.2188158  0.0382374 -5.7226 1.354e-08 ***
log(density)      4.3241239  1.7998941  2.4024 0.0164524 *
avginc            0.0168302  0.0084724  1.9865 0.0472300 *
log(pop)         -4.1924921  1.7827682 -2.3517 0.0188658 *
pb1064            0.0236911  0.0150308  1.5762 0.1152766
pm1029            0.0916704  0.0154553  5.9313 4.027e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 39.603
R-Squared:      0.26012
Adj. R-Squared: 0.20664
```

Comparing between FE and Time FE

```
        F test for individual effects

data:  log(rob) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
F = 10.803, df1 = 21, df2 = 1093, p-value < 2.2e-16
alternative hypothesis: significant effects
```

As seen in the screenshot above, the combined effect of the time variables is significant. Thus, we accept the Time FE model over the FE model.

Random Effect Model

```
Rob_RE <- plm(log(rob) ~ shall + factor(year) + log(incarc_rate) + log(density) + avginc +
                    log(pop) + pb1064 + pm1029, index=c("stateid","year"), model = "random", data = Data)


phtest(Rob_Time_FE, Rob_RE)
```

```
        Hausman Test

data:  log(rob) ~ shall + factor(year) + log(incarc_rate) + log(density) +  ...
chisq = 83.391, df = 29, p-value = 3.655e-07
alternative hypothesis: one model is inconsistent
```

We reject the Null Hypothesis and observe that the RE model has endogeneity. Therefore, we reject the RE model.

Interpretation of Selected Model: Entity-Time Fixed Model

According to the Entity-Time Fixed Model, we see that having the shall-issue law decreases robbery rates by 0.282%. However, this is not significant even at a 90% confidence level. Thus, we cannot make any statistically significant conclusion about the effect of shall-issue laws on robbery rates.

Increasing the incarceration rate by 1% reduces the robbery rates by 0.218% and is significant at a 99% confidence level. Having a unit percent increase in males between 10-29 (having a unit increase in pm1029) increases the robbery rates by 9.16% and is significant at a 99% confidence level.

The effects of average income, population and density are statistically insignificant at a 99% confidence level but significant at a 95% confidence level. An increase in density by 1% results in an increase of 4.32% in the robbery rate. An increase in average income by 1,000$ results in an increase of 1.68% in the robbery rate. An increase in population by 1% results in a decrease of 4.19% in the robbery rate.

The effect of percentage of black people between the age of 10 to 64 is statistically insignificant at a 90% confidence level.

Overall Comparison Between Pooled, Fixed, Time-Entity Fixed And Random Effect Models

For robbery rate and murder rate, we see that the Time-Entity Fixed model is the most appropriate. For violent crimes rate, we see that the Random Effect model is the most appropriate.

For all our independent variables, we reject the pooled effects model because of endogeneity issues. Between the fixed and time-entity fixed model, we choose the time-entity fixed model as the combined effect of the year indicator variables is significant.

Between fixed and random effect model, we performed the Hausman test, we see that the random effect model has endogeneity issues for robbery rate and murder rate and does not have endogeneity issues for violent crimes rate.

Limitations of Entity and Time Fixed Effect Models

Simultaneous Causality Bias

There can be simultaneous causality bias between incarceration and crime rates. If we increased incarceration rate, it should reduce crime rates. However, if crime rate goes up and law enforcement becomes more effective, there will be more prisoners and thus more incarceration. Hence, if there are many crimes this may force the government to change the shall-issue law.

Omitted Variables

There could be omitted variables that could affect the crime rates which simultaneously change with both entities and year. Some of these might be the availability of guns in the state, and efficiency of the local law enforcement or the cultural attitudes of the states.

Conclusion

From our work, we observed that the time-entity fixed effects had the most realistic results for robbery rate and murder rate. For violent crimes rate, we observed that the random effects mode had the most efficient results. The phenomenon of omitted variable bias and unobserved heterogeneity has been accounted for (for the most part).

We conclude from our interpretations that there is no significant effect of the shall-issue law on all our independent variables (violent crimes rate, robbery rate and murder rate) at a 95% significance level.