Analyzing the Impact of Shall Law on Crime Rates A Statistical Approach

By,
Anushka Poddaturi

Data Description:

The "Guns.dta" dataset comprises 1,137 observations, each representing a state in a specific year from 1977 to 1999. It includes 13 variables, with 11 numeric and 2 categorical variables. "Stateid" serves as the state identifier, and "Shall" is a binary variable (1 for a state with a shall-carry law in effect). The dataset covers 51 unique states and provides valuable insights into the presence of shall-carry laws and other gun-related characteristics over time.

Data Exploration:

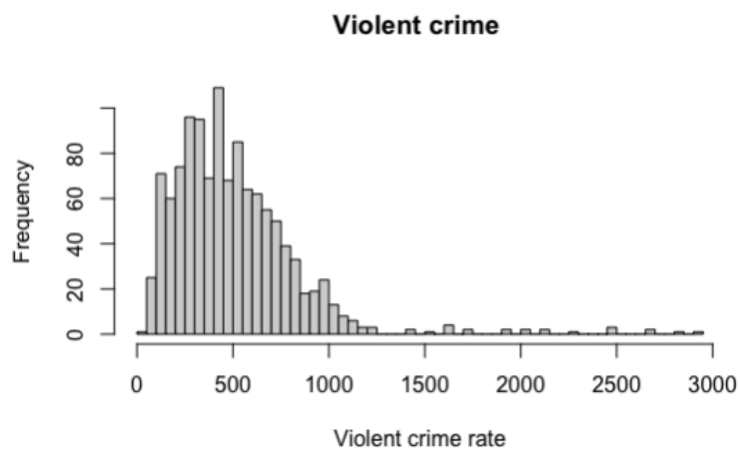
The data has no missing values.

```
> #checking if there are null values
> sum(is.na(data_gun))
[1] 0
```

Exploratory Data Analysis

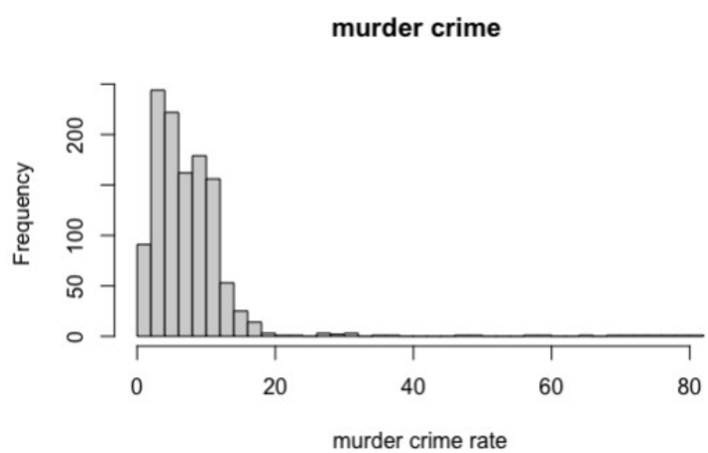
Violence crime rate(incidents per 100,000 population)

The violence crime rate in the dataset, measured in incidents per 100,000 population, exhibits a left-skewed distribution. The mean violence crime rate is 503.1, with a median of 443, reflecting the presence of lower-frequency high-incidence values. The range of violence crime rates spans from a minimum of 47 to a maximum of 2921.8 incidents per 100,000 population. The skewness value of 2.538371 further confirms the leftward skew in the distribution. Notably, 75% of the violence crime rate values fall below 650.9, highlighting the concentration of most observations in the lower range of crime rates.



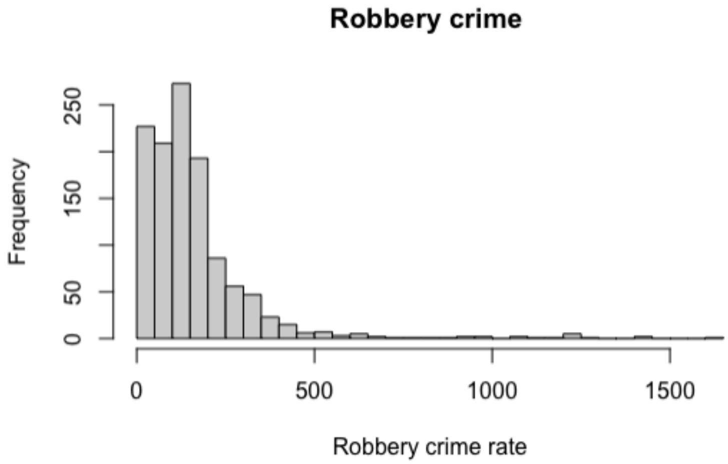
Murder rate(incidents per 100,000 population)

The dataset reveals a left-skewed distribution in the murder rate, with a mean of 7.665 and a strongly left-skewed skewness value of 5.785826. The range spans from 0.2 to 80.6 incidents per 100,000 population, and 75% of the values are below 9.80, highlighting the prevalence of lower-range murder rates.



Robbery Rate(incidents per 100,000 population)

The dataset indicates a left-skewed distribution in the robbery rate, with a mean of 161.8 and a median of 124.1. The range extends from 6.4 to 1635.1, demonstrating variability in robbery rates. The skewness value of 3.882311 confirms the leftward skew, and notably, 75% of the observations fall below 192.7, emphasizing the concentration of most robbery rates in the lower range.

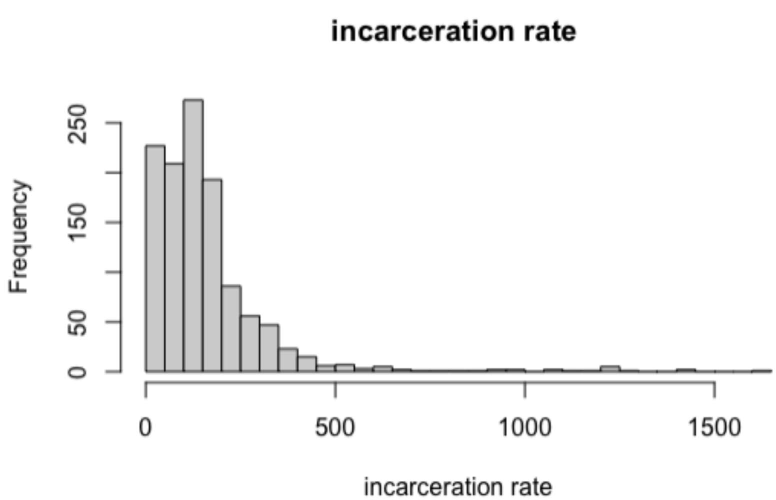


Shall

Shall is a binary variable denoting the presence of a shall-carry law in a given state and year. A value of 1 indicates the existence of such a law, while a value of 0 signifies the absence of a shall-carry law during that specific year.

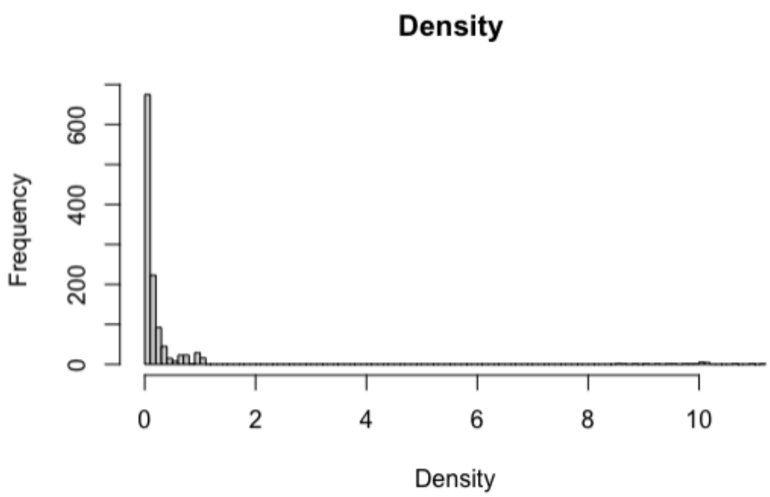
Incarceration rate(sentenced prisoners per 100,000 residents; value for the previous year)

The incarceration rate, measuring sentenced prisoners per 100,000 residents in the previous year, exhibits a left-skewed distribution with a mean of 226.6 and a median of 187. Ranging from 19 to 1913, the skewness value of 3.881709 confirms the leftward skew, and 75% of values fall below 291, emphasizing the prevalence of lower-range incarceration rates in the dataset.



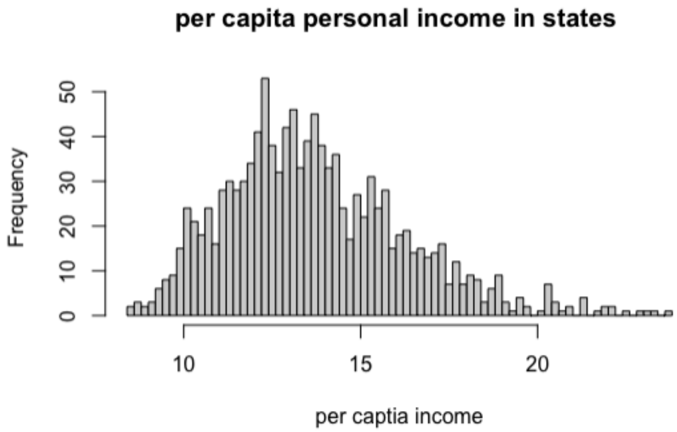
Density(population per square mile of land area, divided by 1000)

The variable "Density" in the dataset, with a mean of 0.352038 and a strongly left-skewed distribution (skewness value: 6.694125), exhibits significant variability ranging from 0.000707 to 11.102116. Notably, 75% of the values fall below 0.177718, emphasizing the prevalence of lower-range density values.



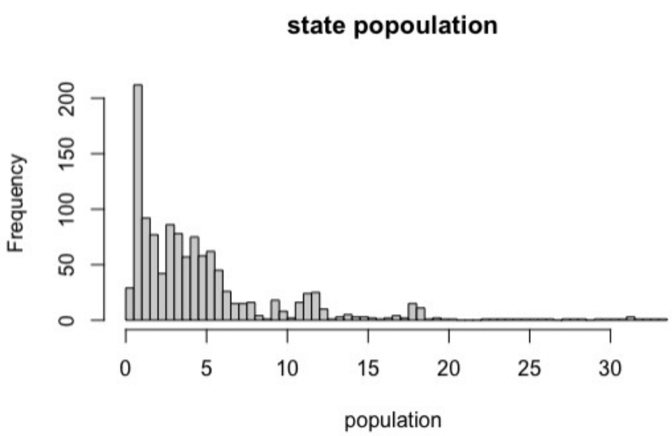
avginc(in thousands of dollars)

The variable "avginc," representing real per capita personal income in thousands of dollars, exhibits a distribution with a mean of 13.725 and a median of 13.402. Ranging from a minimum of 8.555 to a maximum of 23.647, it shows variability. Notably, 75% of "avginc" values fall below 15.271, highlighting the concentration of the majority of observations in the lower range of real per capita personal income.



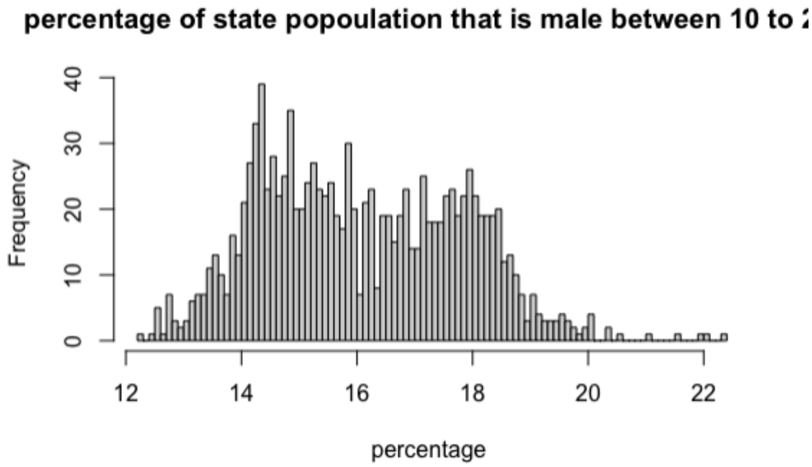
Pop

The variable "Pop," representing state population in millions of people, demonstrates a distribution with a mean of 4.8163 and a median of 3.2713. Ranging from a minimum of 0.4027 to a maximum of 33.1451, it indicates considerable variability. Notably, 75% of "Pop" values fall below 5.6856, emphasizing the concentration of the majority of state populations in the lower range.



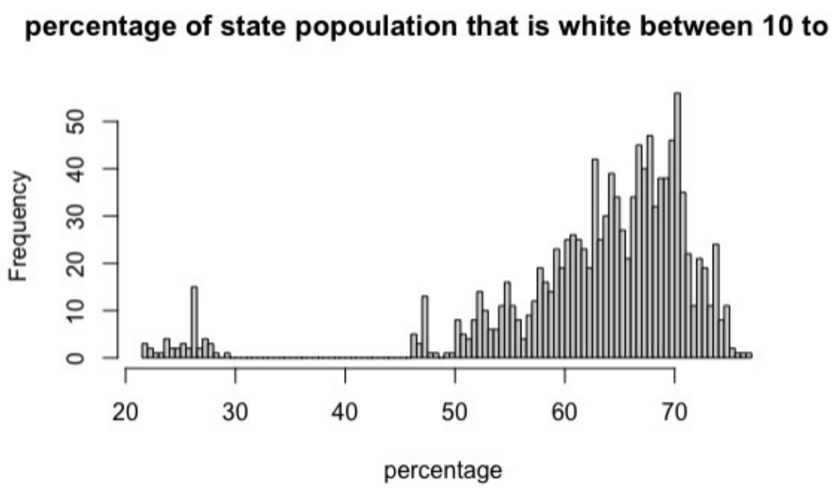
Pm1209

The variable "pm1029," indicating the percent of the state population that is male, ages 10 to 29, exhibits a distribution with a mean of 16.08 and a median of 15.90. Ranging from a minimum of 12.21 to a maximum of 22.35, it suggests variability. Notably, 75% of "pm1029" values fall below 17.53, emphasizing the prevalence of lower-range percentages in this demographic group.



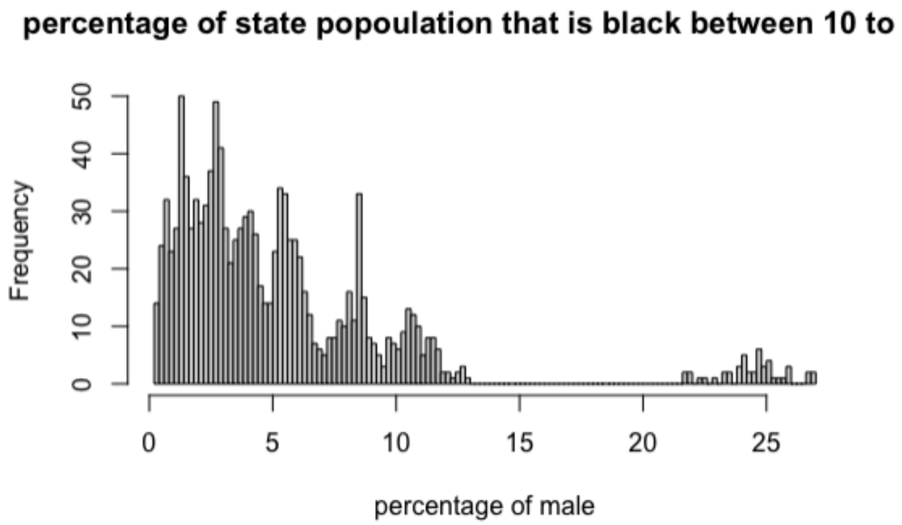
Pw1064

The variable "pw1064," reflecting the percent of the state population that is white, ages 10 to 64, demonstrates a distribution with a mean of 62.95 and a median of 65.06. Ranging from a minimum of 21.78 to a maximum of 76.53, it suggests variability. The right-skewed distribution is evident, with 75% of "pw1064" values falling below 69.20, indicating a concentration toward the lower end of the percentage range.



Pb1064

The variable "pb1064," signifying the percent of the state population that is black, ages 10 to 64, displays a distribution with a mean of 5.3362 and a median of 4.0262. The range spans from a minimum of 0.2482 to a maximum of 26.9796, indicating variability. The left-skewed distribution is evident, with 75% of "pb1064" values falling below 6.8507, emphasizing a concentration toward the higher end of the percentage range.



Stateid

Stateid is a categorical variable assigning numerical identifiers to each state based on alphabetical order, encompassing 50 states and the District of Columbia, totaling 51 unique values.

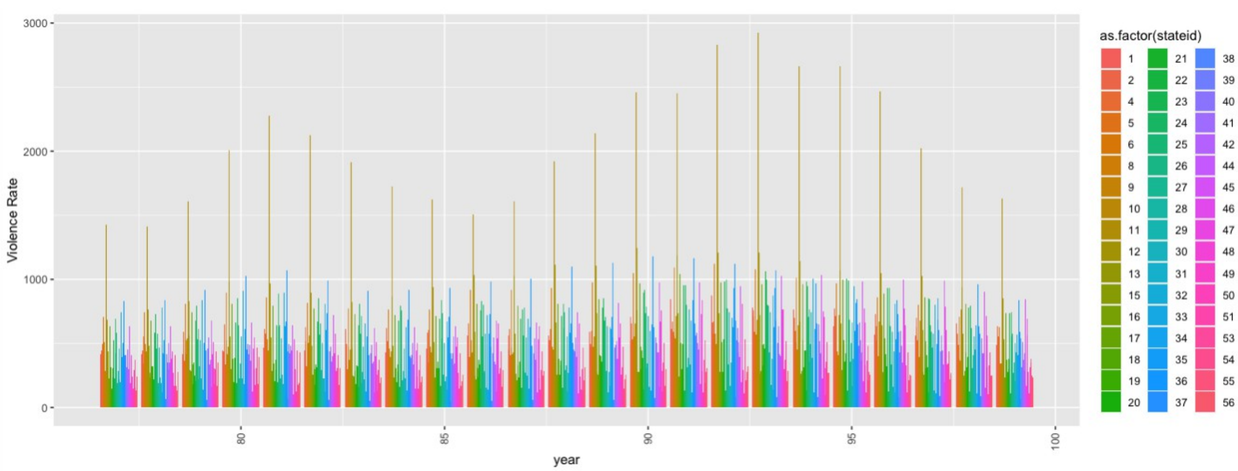
Year

The dataset spans observations for all states from 1977 to 1999, providing a comprehensive temporal perspective.

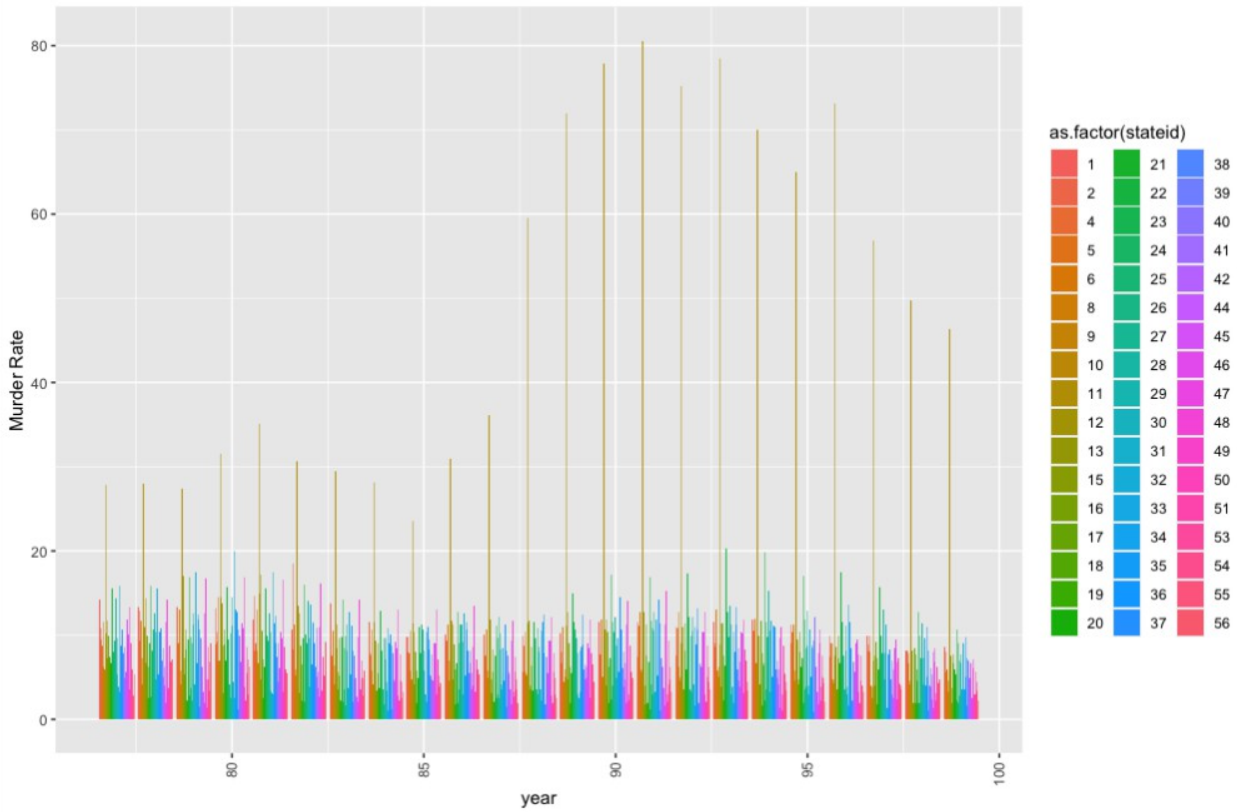
```
> summary(data_gun)
      year          vio              mur               rob            incarc_rate        pb1064
 Min.    :77   Min.    :  47.0   Min.    : 0.200   Min.    :   6.4   Min.    :  19.0   Min.    : 0.2482
 1st Qu.:82   1st Qu.: 283.1   1st Qu.: 3.700   1st Qu.:  71.1   1st Qu.: 114.0   1st Qu.: 2.2022
 Median :88   Median : 443.0   Median : 6.400   Median : 124.1   Median : 187.0   Median : 4.0262
 Mean   :88   Mean   : 503.1   Mean   : 7.665   Mean   : 161.8   Mean   : 226.6   Mean   : 5.3362
 3rd Qu.:94   3rd Qu.: 650.9   3rd Qu.: 9.800   3rd Qu.: 192.7   3rd Qu.: 291.0   3rd Qu.: 6.8507
 Max.   :99   Max.    :2921.8   Max.    :80.600   Max.    :1635.1   Max.    :1913.0   Max.    :26.9796
     pw1064          pm1029           pop              avginc          density            stateid
 Min.    :21.78   Min.    :12.21   Min.    : 0.4027   Min.    : 8.555   Min.    : 0.000707   Min.    : 1.00
 1st Qu.:59.94   1st Qu.:14.65   1st Qu.: 1.1877   1st Qu.:11.935   1st Qu.: 0.031911   1st Qu.:16.00
 Median :65.06   Median :15.90   Median : 3.2713   Median :13.402   Median : 0.081569   Median :29.00
 Mean   :62.95   Mean   :16.08   Mean   : 4.8163   Mean   :13.725   Mean   : 0.352038   Mean   :28.96
 3rd Qu.:69.20   3rd Qu.:17.53   3rd Qu.: 5.6856   3rd Qu.:15.271   3rd Qu.: 0.177718   3rd Qu.:42.00
 Max.   :76.53   Max.    :22.35   Max.    :33.1451   Max.    :23.647   Max.    :11.102116   Max.    :56.00
     shall
 Min.    :0.000
 1st Qu.:0.000
 Median :0.000
 Mean   :0.243
 3rd Qu.:0.000
 Max.   :1.000
```

Visualisations:

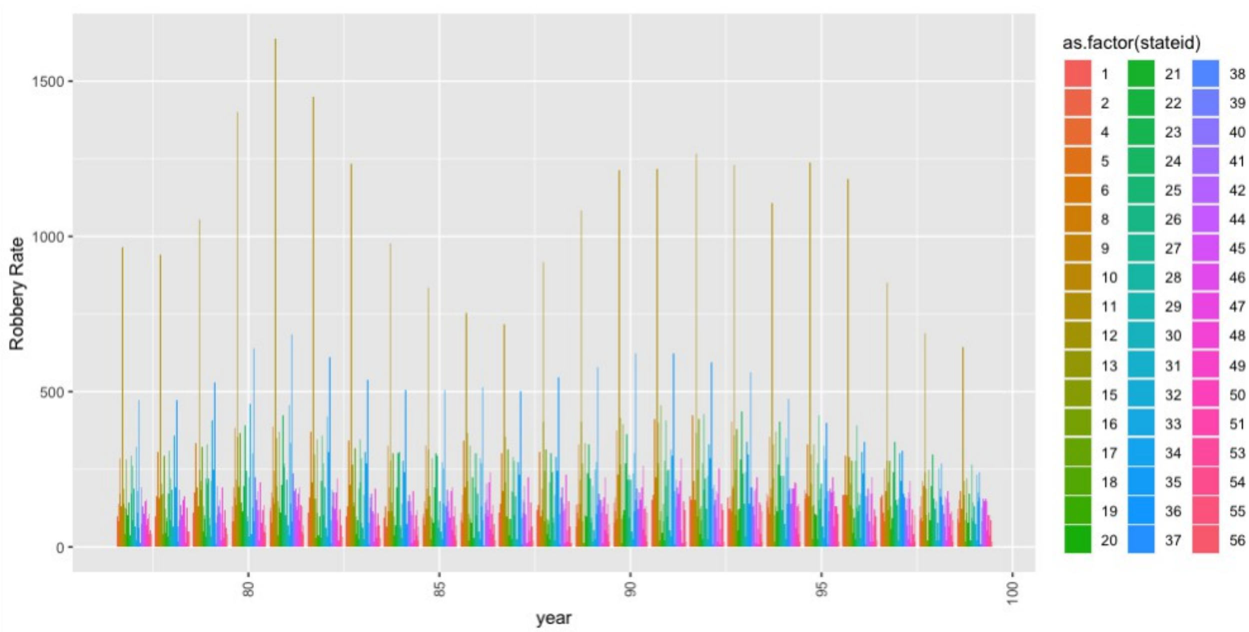
Violence rate vs year for each state



Murder rate vs year for each state

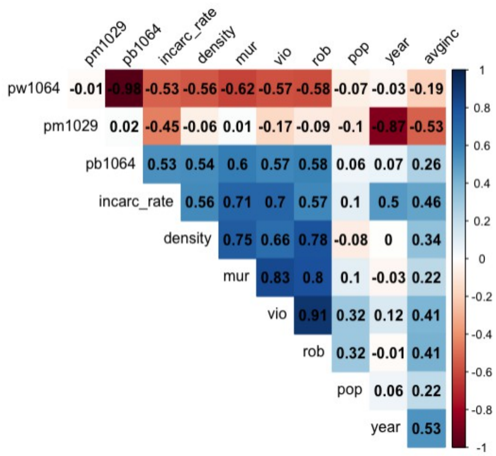


Robbery rate vs year for each state



State id =11 is an outlier in the data. It causes skewness in the data.

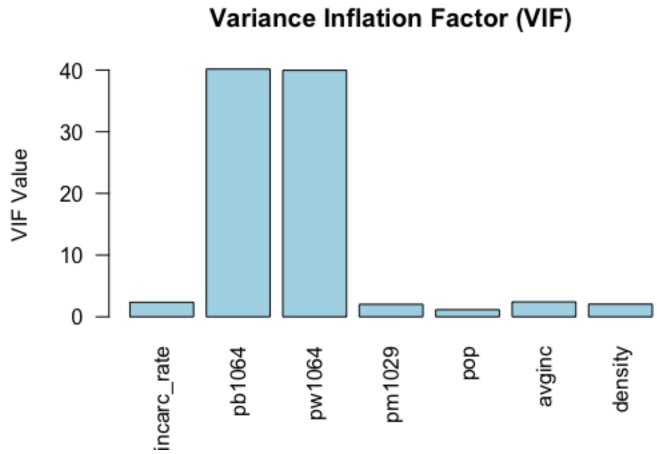
Correlation Matrix



- Negative correlations exist between "pw1064" and murder rate, violence rate, and robbery rate, suggesting lower involvement of white males aged 10 to 64 in these crimes.
- Positive correlations, exceeding 0.5, between "pb1064" and murder rate, violence rate, and robbery rate indicate a higher likelihood of involvement among black males.
- Positive and substantial correlations between "density" and crime rates (murder, violence, and robbery) suggest that states with higher population density tend to have elevated crime rates.
- Strong positive correlations between crime rates themselves, such as 0.83 for murder and violence, and 0.91 for violence and robbery, highlight interconnected crime dynamics.
- Positive correlations between crime rates and "avginc" (average income) suggest that as per capita income increases, so does the incidence of violence and robbery.
- The correlation between "year" and "avginc" at 0.53 implies a consistent rise in per capita income over the observed years.

Multicollinearity and Endogeneity

We can see using a variance inflation factor measure that there are varying degrees of multicollinearity among the predictor variables in your model. VIF basically assesses the degree of multicollinearity among the independent variables in a regression model. For the predictor variables below are the VIF values and what they indicate:



2. Moderate Multicollinearity:
- incarc_rate (Incarceration Rate): VIF = 2.35
- pm1029 (Percent of the State Population that is Male): VIF = 2.02
- avginc (Average Income): VIF = 2.41
- density (Population Density): VIF = 2.04

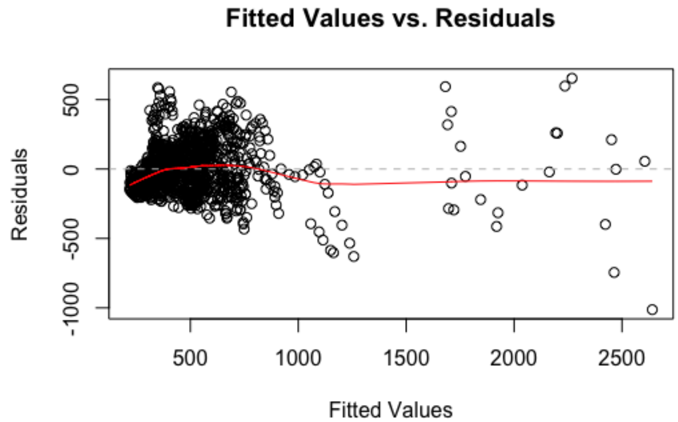
For these variables, the VIF values are moderately elevated (between 2 and 5), suggesting some correlation with other predictors but not to an alarming degree.

2. High Multicollinearity:
- pb1064 (Percent of the State Population that is black): VIF = 40.15
- pw1064 (Percent of the State Population that is white): VIF = 39.96

These variables exhibit high VIF values, indicating a strong correlation with other predictors. High multicollinearity can lead to issues in the estimation and interpretation of regression coefficients. From the above multicollinearity values, we can remove the variables pb1604 and pw1604 when assessing "Violent Crime Rate" model due to very high correlation between them. To deal with multicollinearity we will be exploring models which will regularize the variables.

Endogeneity is a scenario when a variable in a statistical model is related to the error term of the model. This correlation leads to bias in coefficient estimates, complicating the ability to draw valid inferences about variable relationships. Additionally, it may result in underestimated standard errors, potentially leading to inaccurate assessments of the statistical significance of the coefficients.

Below is a plot showing the residuals on the y-axis and the fitted values on the x-axis. This plot is useful for identifying patterns or trends in the residuals.



Observing the plot above, we can say that there is almost no heteroscedasticity, only for some of the extreme values the residuals are bit more than other variables.

Regression Models For Reference

Question: "Do shall-issues law reduce crime-or not?"

We must see that if a shall law is in effect in a state for a given year the crime rate should decrease.

Null hypothesis: $\beta_{shall} > 0$

Alternative hypothesis: $\beta_{shall} < 0$

We decide to form three different models with the three dependent variables.

Regression model for violence rate

```
> summary(model1)

Call:
lm(formula = data_gun$vio ~ data_gun$year + data_gun$shall +
    data_gun$incarc_rate + data_gun$pb1064 + data_gun$pw1064 +
    data_gun$pm1029 + data_gun$pop + data_gun$avginc + data_gun$density +
    data_gun$stateid, data = data_gun)

Residuals:
    Min      1Q  Median      3Q     Max
-798.71  -46.75    0.54   42.37  770.16

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           501.92327  268.06626   1.872 0.061415 .
data_gun$year          -5.55636    2.61012  -2.129 0.033492 *
data_gun$shall1       -12.89302   11.84949  -1.088 0.276802
data_gun$incarc_rate    0.13163    0.05957   2.210 0.027330 *
data_gun$pb1064        28.35787   13.09256   2.166 0.030527 *
data_gun$pw1064        15.36291    3.90470   3.934 8.85e-05 ***
data_gun$pm1029       -39.16046    8.18465  -4.785 1.94e-06 ***
data_gun$pop           14.06230    5.40619   2.601 0.009414 **
data_gun$avginc        -0.50536    3.98367  -0.127 0.899075
data_gun$density     -144.63453   52.30613  -2.765 0.005784 **
data_gun$stateid2      82.48480   44.71260   1.845 0.065335 .
data_gun$stateid4      47.35957   55.48602   0.854 0.393543
data_gun$stateid5     -97.08809   42.07644  -2.307 0.021214 *
data_gun$stateid6      -0.71078  142.64753  -0.005 0.996025
data_gun$stateid8    -113.58632   68.93184  -1.648 0.099675 .
data_gun$stateid9     -96.01648   83.10726  -1.155 0.248202
data_gun$stateid10     54.98606   47.24111   1.164 0.244696
data_gun$stateid11   2871.90695  490.70679   5.853 6.36e-09 ***
data_gun$stateid12    320.13077   70.45019   4.544 6.12e-06 ***
data_gun$stateid13     13.59823   34.11721   0.399 0.690284
data_gun$stateid15   -200.03067  164.86150  -1.213 0.225263
data_gun$stateid16   -241.30837   79.33551  -3.042 0.002408 **
data_gun$stateid17    179.81375   66.00215   2.724 0.006543 **
data_gun$stateid18   -172.47999   68.27552  -2.526 0.011667 *
data_gun$stateid19   -298.59822   80.59750  -3.705 0.000222 ***
data_gun$stateid20   -148.28770   63.93122  -2.319 0.020549 *
data_gun$stateid21   -231.98999   65.82604  -3.524 0.000442 ***
data_gun$stateid22    252.65899   35.07776   7.203 1.08e-12 ***
data_gun$stateid23   -397.44241   82.93004  -4.793 1.87e-06 ***
data_gun$stateid24    296.03208   42.97653   6.888 9.43e-12 ***
```

```
data_gun$stateid25    102.53869   91.18516   1.125 0.261039
data_gun$stateid26     53.92579   60.75334   0.888 0.374938
data_gun$stateid27   -289.68947   77.79327  -3.724 0.000206 ***
data_gun$stateid28   -115.30238   47.39513  -2.433 0.015140 *
data_gun$stateid29     -9.90528   56.72312  -0.175 0.861406
data_gun$stateid30   -359.72957   66.23942  -5.431 6.89e-08 ***
data_gun$stateid31   -223.72250   72.65062  -3.079 0.002125 **
data_gun$stateid32    146.13223   53.24167   2.745 0.006154 **
data_gun$stateid33   -415.00890   86.07623  -4.821 1.62e-06 ***
data_gun$stateid34     26.99415   80.32328   0.336 0.736882
data_gun$stateid35    222.22412   49.95633   4.448 9.52e-06 ***
data_gun$stateid36    197.01207   92.50446   2.130 0.033411 *
data_gun$stateid37    -62.93353   33.93408  -1.855 0.063920 .
data_gun$stateid38   -390.36808   74.24255  -5.258 1.75e-07 ***
data_gun$stateid39   -214.60295   76.98665  -2.788 0.005401 **
data_gun$stateid40    -74.15138   42.32639  -1.752 0.080067 .
data_gun$stateid41    -94.11300   70.99239  -1.326 0.185219
data_gun$stateid42   -287.48266   84.05771  -3.420 0.000649 ***
data_gun$stateid44    -39.46975   96.88199  -0.407 0.683792
data_gun$stateid45    264.31111   35.47641   7.450 1.86e-13 ***
data_gun$stateid46   -327.68467   64.34486  -5.093 4.14e-07 ***
data_gun$stateid47     -3.00683   44.10121  -0.068 0.945654
data_gun$stateid48   -120.31620   88.83897  -1.354 0.175910
data_gun$stateid49   -129.46441   80.88760  -1.601 0.109761
data_gun$stateid50   -398.18894   84.42342  -4.717 2.70e-06 ***
data_gun$stateid51   -278.51982   38.96836  -7.147 1.60e-12 ***
data_gun$stateid53   -142.09067   63.43878  -2.240 0.025300 *
data_gun$stateid54   -368.38280   76.65586  -4.806 1.75e-06 ***
data_gun$stateid55   -344.24718   73.14856  -4.706 2.84e-06 ***
data_gun$stateid56   -234.31328   77.28161  -3.032 0.002486 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 98.35 on 1113 degrees of freedom
Multiple R-squared:  0.9178,	Adjusted R-squared:  0.9134
F-statistic: 210.6 on 59 and 1113 DF,  p-value: < 2.2e-16
```

In this model coefficient of shall is -12.89302 and p-value is 0.276802.We conclude that at 95% confidence we cannot reject the null hypothesis. This means that shall -issue law might not have no effect on crime rate.

Regression model for murder rate

```
> summary(model2)

Call:
lm(formula = data_gun$mur ~ data_gun$year + data_gun$shall +
    data_gun$incarc_rate + data_gun$pb1064 + data_gun$pw1064 +
    data_gun$pm1029 + data_gun$pop + data_gun$avginc + data_gun$density +
    data_gun$stateid, data = data_gun)

Residuals:
     Min       1Q   Median       3Q      Max
-23.9989  -0.8911  -0.0181   0.8127  28.1716

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           29.698817   7.315290   4.060 5.25e-05 ***
data_gun$year         -0.323581   0.071228  -4.543 6.15e-06 ***
data_gun$shall1       -0.324157   0.323362  -1.002 0.316341
data_gun$incarc_rate   0.009956   0.001626   6.124 1.26e-09 ***
data_gun$pb1064       -0.877649   0.357284  -2.456 0.014184 *
data_gun$pw1064        0.222446   0.106556   2.088 0.037061 *
data_gun$pm1029       -0.303793   0.223352  -1.360 0.174056
data_gun$pop          -0.415401   0.147530  -2.816 0.004953 **
data_gun$avginc        0.791296   0.108711   7.279 6.35e-13 ***
data_gun$density      -6.166271   1.427388  -4.320 1.70e-05 ***
data_gun$stateid2     -8.698765   1.220167  -7.129 1.81e-12 ***
data_gun$stateid4    -10.325229   1.514164  -6.819 1.50e-11 ***
data_gun$stateid5     -5.709109   1.148229  -4.972 7.67e-07 ***
data_gun$stateid6      5.058850   3.892724   1.300 0.194019
data_gun$stateid8    -16.035654   1.881089  -8.525  < 2e-16 ***
data_gun$stateid9    -14.882252   2.267923  -6.562 8.12e-11 ***
data_gun$stateid10   -12.062456   1.289168  -9.357  < 2e-16 ***
data_gun$stateid11   104.069868  13.390952   7.772 1.75e-14 ***
data_gun$stateid12    -2.473745   1.922523  -1.287 0.198460
data_gun$stateid13     1.954746   0.931028   2.100 0.035993 *
data_gun$stateid15    12.457173   4.498924   2.769 0.005718 **
data_gun$stateid16   -17.912138   2.164995  -8.274 3.68e-16 ***
data_gun$stateid17    -2.914646   1.801140  -1.618 0.105898
data_gun$stateid18   -10.455669   1.863178  -5.612 2.53e-08 ***
data_gun$stateid19   -19.248102   2.199434  -8.751  < 2e-16 ***
data_gun$stateid20   -14.577461   1.744626  -8.356  < 2e-16 ***
data_gun$stateid21   -10.687104   1.796334  -5.949 3.60e-09 ***
data_gun$stateid22     6.651663   0.957241   6.949 6.26e-12 ***
data_gun$stateid23   -19.619455   2.263087  -8.669  < 2e-16 ***
data_gun$stateid24    -0.671726   1.172791  -0.573 0.566924
```

```
data_gun$stateid25   -12.962458   2.488362  -5.209 2.26e-07 ***
data_gun$stateid26    -5.244201   1.657905  -3.163 0.001603 **
data_gun$stateid27   -17.940060   2.122909  -8.451  < 2e-16 ***
data_gun$stateid28     6.632869   1.293371   5.128 3.45e-07 ***
data_gun$stateid29    -8.415666   1.547924  -5.437 6.67e-08 ***
data_gun$stateid30   -16.254594   1.807615  -8.992  < 2e-16 ***
data_gun$stateid31   -17.794891   1.982571  -8.976  < 2e-16 ***
data_gun$stateid32   -10.480796   1.452918  -7.214 1.01e-12 ***
data_gun$stateid33   -21.537506   2.348944  -9.169  < 2e-16 ***
data_gun$stateid34    -5.833353   2.191951  -2.661 0.007897 **
data_gun$stateid35    -6.460369   1.363264  -4.739 2.43e-06 ***
data_gun$stateid36     1.553565   2.524365   0.615 0.538398
data_gun$stateid37    -1.228161   0.926031  -1.326 0.185024
data_gun$stateid38   -18.072290   2.026013  -8.920  < 2e-16 ***
data_gun$stateid39    -8.822522   2.100897  -4.199 2.89e-05 ***
data_gun$stateid40    -8.601861   1.155050  -7.447 1.91e-13 ***
data_gun$stateid41   -16.740238   1.937319  -8.641  < 2e-16 ***
data_gun$stateid42    -8.374425   2.293860  -3.651 0.000274 ***
data_gun$stateid44   -12.603765   2.643823  -4.767 2.11e-06 ***
data_gun$stateid45     0.865794   0.968120   0.894 0.371352
data_gun$stateid46   -17.070126   1.755914  -9.722  < 2e-16 ***
data_gun$stateid47    -4.650466   1.203483  -3.864 0.000118 ***
data_gun$stateid48     0.255032   2.424337   0.105 0.916239
data_gun$stateid49   -15.521634   2.207351  -7.032 3.55e-12 ***
data_gun$stateid50   -20.264894   2.303840  -8.796  < 2e-16 ***
data_gun$stateid51    -5.344685   1.063412  -5.026 5.83e-07 ***
data_gun$stateid53   -14.104897   1.731188  -8.148 9.91e-16 ***
data_gun$stateid54   -13.928022   2.091870  -6.658 4.35e-11 ***
data_gun$stateid55   -15.712214   1.996159  -7.871 8.29e-15 ***
data_gun$stateid56   -19.005382   2.108947  -9.012  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.684 on 1113 degrees of freedom
Multiple R-squared:  0.8791,    Adjusted R-squared:  0.8727
F-statistic: 137.2 on 59 and 1113 DF,  p-value: < 2.2e-16
```

In this model coefficient of shall is - 0.324157 and p-value is 0.316341.We conclude that at 95% confidence we cannot reject the null hypothesis. This means that shall -issue law might not have no effect on crime rate.

Regression model for robbery rate

```
> summary(model3)

Call:
lm(formula = data_gun$rob ~ data_gun$year + data_gun$shall +
    data_gun$incarc_rate + data_gun$pb1064 + data_gun$pw1064 +
    data_gun$pm1029 + data_gun$pop + data_gun$avginc + data_gun$densi
    data_gun$stateid, data = data_gun)

Residuals:
    Min      1Q  Median      3Q     Max
-367.26  -17.18   -0.86   16.24  470.18

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           -68.88478  131.48477  -0.524 0.600453
data_gun$year          -1.40337    1.28025  -1.096 0.273242
data_gun$shall1         9.33496    5.81210   1.606 0.108530
data_gun$incarc_rate   -0.13270    0.02922  -4.542 6.19e-06 ***
data_gun$pb1064        27.41086    6.42182   4.268 2.14e-05 ***
data_gun$pw1064         6.88353    1.91523   3.594 0.000340 ***
data_gun$pm1029       -11.83875    4.01452  -2.949 0.003255 **
data_gun$pop            3.68229    2.65170   1.389 0.165217
data_gun$avginc        -6.57192    1.95397  -3.363 0.000796 ***
data_gun$density      -59.47164   25.65582  -2.318 0.020627 *
data_gun$stateid2       6.53896   21.93124   0.298 0.765639
data_gun$stateid4     101.16768   27.21553   3.717 0.000211 ***
data_gun$stateid5       1.71992   20.63823   0.083 0.933599
data_gun$stateid6     159.92938   69.96770   2.286 0.022456 *
data_gun$stateid8      56.40789   33.81062   1.668 0.095528 .
data_gun$stateid9     174.46292   40.76357   4.280 2.03e-05 ***
data_gun$stateid10     88.97615   23.17146   3.840 0.000130 ***
data_gun$stateid11   1453.50456  240.68852   6.039 2.11e-09 ***
data_gun$stateid12    217.08956   34.55536   6.282 4.78e-10 ***
data_gun$stateid13     51.20884   16.73427   3.060 0.002265 **
data_gun$stateid15   -223.72841   80.86350  -2.767 0.005756 **
data_gun$stateid16     -7.14404   38.91355  -0.184 0.854371
data_gun$stateid17    220.31619   32.37363   6.805 1.64e-11 ***
data_gun$stateid18     37.35555   33.48870   1.115 0.264891
data_gun$stateid19      8.27773   39.53256   0.209 0.834182
data_gun$stateid20     51.14614   31.35785   1.631 0.103163
data_gun$stateid21     14.58140   32.28725   0.452 0.651634
data_gun$stateid22     82.50133   17.20542   4.795 1.85e-06 ***
data_gun$stateid23    -32.38368   40.67665  -0.796 0.426129
data_gun$stateid24    229.76253   21.07971  10.900  < 2e-16 ***
data_gun$stateid25    154.30955   44.72573   3.450 0.000581 ***
```

```
data_gun$stateid25    154.30955   44.72573   3.450 0.000581 ***
data_gun$stateid26    142.95132   29.79912   4.797 1.83e-06 ***
data_gun$stateid27     42.81333   38.15710   1.122 0.262093
data_gun$stateid28    -71.36341   23.24701  -3.070 0.002194 **
data_gun$stateid29    116.63596   27.82232   4.192 2.98e-05 ***
data_gun$stateid30    -40.56617   32.49001  -1.249 0.212084
data_gun$stateid31     20.68421   35.63466   0.580 0.561727
data_gun$stateid32    260.75595   26.11470   9.985  < 2e-16 ***
data_gun$stateid33    -17.21689   42.21984  -0.408 0.683505
data_gun$stateid34    206.88741   39.39805   5.251 1.81e-07 ***
data_gun$stateid35     43.83602   24.50326   1.789 0.073889 .
data_gun$stateid36    370.46292   45.37284   8.165 8.65e-16 ***
data_gun$stateid37    -15.27888   16.64445  -0.918 0.358841
data_gun$stateid38    -41.06495   36.41549  -1.128 0.259699
data_gun$stateid39     92.00265   37.76146   2.436 0.014990 *
data_gun$stateid40     30.31643   20.76082   1.460 0.144498
data_gun$stateid41     87.84685   34.82131   2.523 0.011781 *
data_gun$stateid42     66.67993   41.22976   1.617 0.106102
data_gun$stateid44    108.42636   47.51999   2.282 0.022695 *
data_gun$stateid45     -9.38833   17.40095  -0.540 0.589629
data_gun$stateid46    -35.48350   31.56074  -1.124 0.261131
data_gun$stateid47     74.67371   21.63136   3.452 0.000577 ***
data_gun$stateid48     89.02959   43.57494   2.043 0.041274 *
data_gun$stateid49     41.20988   39.67485   1.039 0.299174
data_gun$stateid50    -32.71756   41.40914  -0.790 0.429635
data_gun$stateid51    -12.33405   19.11373  -0.645 0.518867
data_gun$stateid53     39.33703   31.11631   1.264 0.206425
data_gun$stateid54    -31.50386   37.59920  -0.838 0.402274
data_gun$stateid55     27.21116   35.87890   0.758 0.448362
data_gun$stateid56     -3.43169   37.90613  -0.091 0.927881
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 48.24 on 1113 degrees of freedom
Multiple R-squared:  0.924,     Adjusted R-squared:   0.92
F-statistic: 229.3 on 59 and 1113 DF,  p-value: < 2.2e-16
```

In this model coefficient of shall is 9.33496 and p-value is 0.108530.In this model shall coefficient shows that when it is in effect robbery rate increases. But at 95% confidence we cannot reject the null hypothesis. This means that shall-issue law might not have no effect on crime rate.

But in our dataset the three dependent variables have high correlation. Hence, We have decided to create a new variable total violence which is summation of violence, crime, and robbery. This gives us a better model as we can see the real impact of shall-issue law on violence ,crime and murder rate. Since the units of violence, crime and murder rate same we can just sum them up.

Regression model for Total Violence

```
> summary(model4)

Call:
lm(formula = data_gun$total_vio ~ data_gun$year + data_gun$shall +
    data_gun$incarc_rate + data_gun$pb1064 + data_gun$pw1064 +
    data_gun$pm1029 + data_gun$pop + data_gun$avginc + data_gun$density +
    data_gun$stateid, data = data_gun)

Residuals:
     Min       1Q   Median       3Q      Max
-1163.27   -62.06    -1.22    54.77  1002.50

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          4.627e+02  3.865e+02   1.197 0.231447
data_gun$year       -7.283e+00  3.763e+00  -1.935 0.053191 .
data_gun$shall1     -3.882e+00  1.708e+01  -0.227 0.820277
data_gun$incarc_rate  8.881e-03  8.588e-02   0.103 0.917656
data_gun$pb1064      5.489e+01  1.888e+01   2.908 0.003710 **
data_gun$pw1064      2.247e+01  5.630e+00   3.991 7.00e-05 ***
data_gun$pm1029     -5.130e+01  1.180e+01  -4.348 1.50e-05 ***
data_gun$pop         1.733e+01  7.794e+00   2.223 0.026397 *
data_gun$avginc     -6.286e+00  5.743e+00  -1.094 0.273992
data_gun$density    -2.103e+02  7.541e+01  -2.788 0.005389 **
data_gun$stateid2    8.032e+01  6.446e+01   1.246 0.213015
data_gun$stateid4    1.382e+02  8.000e+01   1.728 0.084340 .
data_gun$stateid5   -1.011e+02  6.066e+01  -1.666 0.095958 .
data_gun$stateid6    1.643e+02  2.057e+02   0.799 0.424594
data_gun$stateid8   -7.321e+01  9.938e+01  -0.737 0.461468
data_gun$stateid9    6.356e+01  1.198e+02   0.530 0.595874
data_gun$stateid10   1.319e+02  6.811e+01   1.937 0.053051 .
data_gun$stateid11   4.429e+03  7.075e+02   6.261 5.45e-10 ***
data_gun$stateid12   5.347e+02  1.016e+02   5.265 1.68e-07 ***
data_gun$stateid13   6.676e+01  4.919e+01   1.357 0.174974
data_gun$stateid15  -4.113e+02  2.377e+02  -1.730 0.083834 .
data_gun$stateid16  -2.664e+02  1.144e+02  -2.329 0.020052 *
data_gun$stateid17   3.972e+02  9.516e+01   4.174 3.22e-05 ***
data_gun$stateid18  -1.456e+02  9.844e+01  -1.479 0.139444
data_gun$stateid19  -3.096e+02  1.162e+02  -2.664 0.007832 **
data_gun$stateid20  -1.117e+02  9.217e+01  -1.212 0.225748
data_gun$stateid21  -2.281e+02  9.491e+01  -2.403 0.016406 *
data_gun$stateid22   3.418e+02  5.057e+01   6.759 2.24e-11 ***
data_gun$stateid23  -4.494e+02  1.196e+02  -3.759 0.000179 ***
data_gun$stateid24   5.251e+02  6.196e+01   8.475  < 2e-16 ***
```

```
data_gun$stateid25    2.439e+02  1.315e+02   1.855 0.063844 .
data_gun$stateid26    1.916e+02  8.759e+01   2.188 0.028891 *
data_gun$stateid27   -2.648e+02  1.122e+02  -2.361 0.018393 *
data_gun$stateid28   -1.800e+02  6.833e+01  -2.635 0.008539 **
data_gun$stateid29    9.832e+01  8.178e+01   1.202 0.229551
data_gun$stateid30   -4.166e+02  9.550e+01  -4.362 1.41e-05 ***
data_gun$stateid31   -2.208e+02  1.047e+02  -2.108 0.035228 *
data_gun$stateid32    3.964e+02  7.676e+01   5.164 2.86e-07 ***
data_gun$stateid33   -4.538e+02  1.241e+02  -3.656 0.000268 ***
data_gun$stateid34    2.280e+02  1.158e+02   1.969 0.049176 *
data_gun$stateid35    2.596e+02  7.202e+01   3.604 0.000327 ***
data_gun$stateid36    5.690e+02  1.334e+02   4.267 2.15e-05 ***
data_gun$stateid37   -7.944e+01  4.892e+01  -1.624 0.104716
data_gun$stateid38   -4.495e+02  1.070e+02  -4.199 2.89e-05 ***
data_gun$stateid39   -1.314e+02  1.110e+02  -1.184 0.236653
data_gun$stateid40   -5.244e+01  6.102e+01  -0.859 0.390373
data_gun$stateid41   -2.301e+01  1.024e+02  -0.225 0.822197
data_gun$stateid42   -2.292e+02  1.212e+02  -1.891 0.058878 .
data_gun$stateid44    5.635e+01  1.397e+02   0.403 0.686701
data_gun$stateid45    2.558e+02  5.115e+01   5.001 6.62e-07 ***
data_gun$stateid46   -3.802e+02  9.277e+01  -4.099 4.46e-05 ***
data_gun$stateid47    6.702e+01  6.358e+01   1.054 0.292114
data_gun$stateid48   -3.103e+01  1.281e+02  -0.242 0.808612
data_gun$stateid49   -1.038e+02  1.166e+02  -0.890 0.373731
data_gun$stateid50   -4.512e+02  1.217e+02  -3.707 0.000220 ***
data_gun$stateid51   -2.962e+02  5.618e+01  -5.272 1.62e-07 ***
data_gun$stateid53   -1.169e+02  9.146e+01  -1.278 0.201637
data_gun$stateid54   -4.138e+02  1.105e+02  -3.744 0.000190 ***
data_gun$stateid55   -3.327e+02  1.055e+02  -3.155 0.001647 **
data_gun$stateid56   -2.568e+02  1.114e+02  -2.304 0.021388 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 141.8 on 1113 degrees of freedom
Multiple R-squared:  0.9238,	Adjusted R-squared:  0.9197
F-statistic: 228.6 on 59 and 1113 DF,  p-value: < 2.2e-16
```

In this model coefficient of shall is -10.55237006 and p-value is 0.820277. For 95% confidence, we cannot reject the null hypothesis. This means that shall-issue law might not have no effect on crime rate.

However, this is models are for our . We are going to further use panel data and concepts that we used in class for better analysis.

Data Modeling

Analyzing the impact of shall-issue laws on crime reduction necessitates the careful selection of independent and dependent variables. Before conducting any regression analysis, it's important to state the following points:

1) Hypothesis Formulation:

- Null Hypothesis (H0): The impact of shall-issue laws on crime rates is greater than or equal to zero ($\beta Shall\text{–}issue\ Laws \geq 0$).
- Alternative Hypothesis (H1): Shall-issue laws have a negative impact on crime rates ($\beta Shall\text{–}issue\ Laws < 0$).

2) Dependent Variable Selection:

- Considering the high correlation among the individual crime rates (violent crime, murder, and robbery), a composite variable termed 'crime rate' is introduced.
- The 'crime rate' is calculated as the sum of the violent crime rate, murder rate, and robbery rate. By consolidating these measures into a single variable, a more holistic representation of overall criminal activity is achieved.

3) Objective of Modeling:

- The modeling process seeks to evaluate the relationship between shall-issue laws and the newly created 'crime rate' variable.
- This gives us a better understanding if the shall law reduces the crime or not.

Data Transformation

- We first transformed the variable total violence rate to the log form to normalize the skewed distribution.
- We used the variables ln(total_vio) as y and shall,incar_rate,pm1029,pop, avginc,density variables as dependent variables initially to build models.
- Stateid =11 is a outlier as shown in report above, we decided to exclude it in order to get better analysis.
- As shown above in our report pw1064 and pb1064 are correlated with different variables and to avoid the collinearity problem we have excluded that as well.

Types of Models

1) Pooled Model

Model 1 :
Regression Output :

Pooled Model having incarc_rate, , pm1029, pop, avginc, density and shall as independent variables and Log(Totalviolence_rate) as the dependent variable.

```
> model1_ols <- plm(ln_total_vio ~ shall+incarc_rate+pm1029+pop+avginc+density,data = data_gun_without11,model ="pooling",index = c("stateid","year"))
> summary(model1_ols)
Pooling Model

Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + pm1029 + pop +
    avginc + density, data = data_gun_without11, model = "pooling",
    index = c("stateid", "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.721622 -0.268157  0.014333  0.281537  1.023741

Coefficients:
              Estimate  Std. Error  t-value  Pr(>|t|)
(Intercept)  3.99176807  0.22073505  18.0840 < 2.2e-16 ***
shall1      -0.35661251  0.03159854 -11.2857 < 2.2e-16 ***
incarc_rate  0.00287536  0.00012268  23.4376 < 2.2e-16 ***
pm1029       0.07857526  0.00990839   7.9302 5.177e-15 ***
pop          0.04098849  0.00253892  16.1441 < 2.2e-16 ***
avginc       0.01342018  0.00689214   1.9472   0.05176 .
density      0.57003075  0.06568145   8.6787 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    486.24
Residual Sum of Squares: 203.66
R-Squared:      0.58115
Adj. R-Squared: 0.57895
F-statistic: 264.314 on 6 and 1143 DF, p-value: < 2.22e-16
>
```

- Based on the above model, we can see that shall carry law is the very significant variable at the 5% significant level. It shows that with the shall laws in effect, the crime rate drops by 35.66%.
- In reality, the introduction of shall laws is unlikely to lead to such a significant decrease in the crime rate. This observation underscores the need for further analysis, prompting the exploration of alternative models to better understand the complex dynamics at play. As we can see above the variable avginc is not significant. Therefore, in the next step we decided to run a model by removing the insignificant variable avginc.

Model 2 : We have this model without avginc.

Regression Output :

```
Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + pm1029 + pop +
    density, data = data_gun_without11, model = "pooling", index = c("stateid",
    "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.718317 -0.273230  0.011978  0.286336  1.002272

Coefficients:
              Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)  4.2678083  0.1694007  25.1936 < 2.2e-16 ***
shall       -0.3571225  0.0316360 -11.2885 < 2.2e-16 ***
incarc_rate  0.0029104  0.0001215  23.9527 < 2.2e-16 ***
pm1029       0.0715611  0.0092417   7.7433 2.122e-14 ***
pop          0.0417089  0.0025149  16.5849 < 2.2e-16 ***
density      0.6240503  0.0596075  10.4693 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    486.24
Residual Sum of Squares: 204.34
R-Squared:      0.57976
Adj. R-Squared: 0.57792
F-statistic: 315.649 on 5 and 1144 DF, p-value: < 2.22e-16
```

- In the above model, shall is significant at 5 % as well as have the approximately same effect on the dependent variable crime rate as model 1. This is again not practically possible that the mere introduction of the law can reduce the crime rate by almost 36%.
- We feel that here there is omitted variable bias in the model.Therefore, we decided to dig further into individual effect of each of the variable on the crime rate. Based on our analysis, we found below insights.
- Based on insights from EDA, variables such as the incarceration rate, population (pop), and average income (avginc) exhibit a decreasing impact on the total violence rate. To better capture these relationships, quadratic terms for these variables are included in the model.The addition of these squared terms enhances our understanding of non-linear patterns. Additionally, the square of the "density" variable is introduced to provide a more nuanced exploration of its influence on the total violence rate.

Model 3 : We have model 3 in pooled OLS with the quadratic terms.

Regression Output :

```
Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + I(incarc_rate^2) +
    pm1029 + pop + I(pop^2) + density + I(density^2), data = data_gun_without11
    model = "pooling", index = c("stateid", "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.4294780 -0.2308299  0.0028077  0.2473627  1.0542139

Coefficients:
                      Estimate     Std. Error  t-value      Pr(>|t|)
(Intercept)       3.18242362891  0.17002861812  18.7170     < 2.2e-16 ***
shall            -0.26692016397  0.02912604587  -9.1643     < 2.2e-16 ***
incarc_rate       0.00645311151  0.00033932662  19.0174     < 2.2e-16 ***
I(incarc_rate^2) -0.00000630330  0.00000055536 -11.3500     < 2.2e-16 ***
pm1029            0.10498895649  0.00864078766  12.1504     < 2.2e-16 ***
pop               0.09107377170  0.00615582375  14.7947     < 2.2e-16 ***
I(pop^2)         -0.00230085931  0.00023180871  -9.9257     < 2.2e-16 ***
density           1.12492782772  0.19011742777   5.9170 0.00000000433 ***
I(density^2)     -0.60405938431  0.19932902459  -3.0305      0.002497 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    486.24
Residual Sum of Squares: 163.39
R-Squared:      0.66397
Adj. R-Squared: 0.66162
F-statistic: 281.818 on 8 and 1141 DF, p-value: < 2.22e-16
```

- As interpreted the shall law has decreased from 35.7% to 26.6% i.e a drop of almost 10%.Still the reduction of total violence rate when shall law is introduced is still a huge value which is difficult to justify in reality.
- All the variables are significant at 5%.
- We observe that Adjusted R-Squared value has increased from 0.57 to 0.66 after adding the squared terms of the variables that had a downward effect on total violence rate.

However, even though we generated a better model we cannot fix or explain everything. As panel data inherently possesses valuable information unique to each entity and time period, pooled OLS neglects this specificity. To address this limitation, we can develop a model that incorporates fixed effects for both entities and time, thus capturing the nuanced variations across both dimensions.

Entity Fixed Model

Model 1 : FE Model having shall,incarc_rate,pm1029,pop, avgnic and density as independent variables and Log(total_vio) as the dependent variable.

Regression Output

```
Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + pm1029 + pop +
    avginc + density, data = pmdata, model = "within", index = c("stateid",
    "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5855223 -0.1024183  0.0027116  0.1111629  0.5197455

Coefficients:
               Estimate   Std. Error t-value      Pr(>|t|)
shall        0.022624756  0.018364489  1.2320        0.2182
incarc_rate -0.000017412  0.000104432 -0.1667        0.8676
pm1029      -0.035697023  0.006655950 -5.3632 0.00000009974 ***
pop          0.003357987  0.009510048  0.3531        0.7241
avginc      -0.005339903  0.006458517 -0.8268        0.4085
density     -0.025621387  0.607660093 -0.0422        0.9664
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    32.881
Residual Sum of Squares: 29.747
R-Squared:      0.095333
Adj. R-Squared: 0.049852
F-statistic: 19.2142 on 6 and 1094 DF, p-value: < 2.22e-16
```

- From the output we can conclude that effect of the shall on the crime rate has reduced drastically from 26% in the pooled OLS model to just 2.2% but the signs have changed. This model indicates that the shall law increases crime rate by 2.2%.
- Also, the shall law variable is not significant at the 5% or 10% significant level, however we can see that most of the variables are insignificant.
- Using the same concept as pooled OLS , we have included quadratic terms for population, density, avgnic and incarc_rate.

Model 2 : We have this model with the quadratic terms (ln_total_vio ~ shall + incarc_rate + I(incarc_rate^2)+pop+I(pop^2)+ pm1029+density+I(density^2)+avginc+I(avginc^2)

Regression Output :

```
Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + I(incarc_rate^2) +
    pop + I(pop^2) + pm1029 + density + I(density^2) + avginc +
    I(avginc^2), data = pmdata, model = "within", index = c("stateid",
    "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.50576099 -0.09831477 -0.00092557  0.10232997  0.51877065

Coefficients:
                      Estimate     Std. Error  t-value Pr(>|t|)
shall            -0.03827612702  0.01830718938  -2.0908  0.03678 *
incarc_rate       0.00060428982  0.00026379265   2.2908  0.02217 *
I(incarc_rate^2) -0.00000078762  0.00000032418  -2.4296  0.01528 *
pop               0.02954133216  0.02707199876   1.0912  0.27542
I(pop^2)         -0.00080425503  0.00050094903  -1.6055  0.10868
pm1029           -0.00676989531  0.00754598741  -0.8972  0.36984
density           2.23672604838  1.13190612942   1.9761  0.04840 *
I(density^2)      0.04491720129  0.71481239442   0.0628  0.94991
avginc            0.27831581283  0.02551002244  10.9101  < 2e-16 ***
I(avginc^2)      -0.00964574903  0.00082618039 -11.6751  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    32.881
Residual Sum of Squares: 26.073
R-Squared:      0.20706
Adj. R-Squared: 0.16414
F-statistic: 28.4624 on 10 and 1090 DF, p-value: < 2.22e-16
```

- From the output we observe that effect of the shall on the crime rate has decreased to almost 3.8% and now it is significant at 5%.
- However, we can see that most of the variables such as pop,pop.square,incarc_rate I are insignificant and hence it cannot give us a best analysis.
- Now we will build a model by excluding these insignificant variables.

Model 3 : (ln_total_vio ~ shall + pm1029+density+ avginc+I(avginc^2),data=pmdata, model = "within",index = c("stateid","year"))

Regression Output

```
Call:
plm(formula = ln_total_vio ~ shall + pm1029 + density + avginc +
    I(avginc^2), data = pmdata, model = "within", index = c("stateid",
    "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5103225 -0.1005961 -0.0012888  0.1055004  0.5319856

Coefficients:
               Estimate  Std. Error  t-value   Pr(>|t|)
shall       -0.03952087  0.01748317  -2.2605   0.023985 *
pm1029      -0.01610947  0.00554582  -2.9048   0.003749 **
density      2.14414446  0.53792549   3.9860 0.00007166 ***
avginc       0.28225434  0.02464044  11.4549  < 2.2e-16 ***
I(avginc^2) -0.00961403  0.00079855 -12.0394  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    32.881
Residual Sum of Squares: 26.272
R-Squared:      0.20099
Adj. R-Squared: 0.16159
F-statistic: 55.0901 on 5 and 1095 DF, p-value: < 2.22e-16
```

- By omitting the variables which are not significant previously, we observe that the effect of shall law on the crime rate has not changed much but it is significant at 5% level.
- Entity fixed effects model has certain disadvantages. Entity fixed effect models does not consider an omitted variable that might vary over time but not across economic entities. This makes our estimators inefficient.
- In this model the omitted variables might be inflation, GDP, unemployment rate, minimum wage, better gun models in market or improvement in investigation methods by police.

Therefore, we decided to build the Entity and Time fixed effect model.

Entity and Time Fixed Effects

Model 1 : Time FE Model having shall,incarc_rate,pm1029,pop, avgnic and density as independent variables and Log(**total_vio**) as the dependent variable.

Regression Output :

```
Call:
plm(formula = ln_total_vio ~ shall + incarc_rate + pm1029 + pop +
    avginc + density, data = pmdata, effect = "twoways", model = "within",
    index = c("stateid", "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.441850 -0.080779  0.002207  0.086520  0.602980

Coefficients:
               Estimate   Std. Error t-value  Pr(>|t|)
shall       -0.014131862  0.017006202 -0.8310    0.4062
incarc_rate  0.000027932  0.000100521  0.2779    0.7812
pm1029       0.091061719  0.011715327  7.7729 1.791e-14 ***
pop         -0.010208666  0.008222667 -1.2415    0.2147
avginc      -0.005401862  0.007428392 -0.7272    0.4673
density      0.485819156  0.546906977  0.8883    0.3746
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    22.134
Residual Sum of Squares: 20.889
R-Squared:      0.056243
Adj. R-Squared: -0.011545
F-statistic: 10.6477 on 6 and 1072 DF, p-value: 1.6292e-11
```

- In Entity and Time fixed effect model the shall coefficient value is 1.413%,which is very low compared to fixed effect model. In the fixed effect model, the effect of shall law on the crime rate was approximately 3.9%.
- In this model the shall law is not significant even at 10% significant level. Only pm1029 is significant and no other variable is significant at the 5% significant level. Based on what we learned from the prior model, we chose to add the square term of the pop and average income and eliminate the variable incarc_rate.

Model 2 : Time FE Model having shall, pm1029, avgnic , (avginc^2),and density as independent variables and Log(**total_vio**) as the dependent variable.

Regression Output :

```
Call:
plm(formula = ln_total_vio ~ shall + pm1029 + density + avginc +
    I(avginc^2), data = pmdata, effect = "twoways", model = "within",
    index = c("stateid", "year"))

Balanced Panel: n = 50, T = 23, N = 1150

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4662299 -0.0796523  0.0013297  0.0802270  0.5798268

Coefficients:
               Estimate  Std. Error t-value     Pr(>|t|)
shall       -0.04707799  0.01670814 -2.8177     0.004926 **
pm1029       0.06094229  0.01142027  5.3363 0.0000001157 ***
density      1.31715551  0.47367994  2.7807     0.005519 **
avginc       0.22933868  0.02565125  8.9406    < 2.2e-16 ***
I(avginc^2) -0.00735764  0.00078132 -9.4169    < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    22.134
Residual Sum of Squares: 19.322
R-Squared:      0.12703
Adj. R-Squared: 0.065201
F-statistic: 31.2282 on 5 and 1073 DF, p-value: < 2.22e-16
```

- In the above model we observe that the shall carry law has been significant at the 5% significant level. Apart from it all other variables are also significant at the 5% significant level.
- According to the P-Value form the above model, we can conclude that at 5% significant level we can reject the null and accept the alternative hypothesis that shall carry law reduces the crime rate by 4.707% on an average.

pFTest

In order to decide whether Fixed Effects Model is better or Entity and Time Fixed Effects. We ran a f-test.

Model 3 of the FE model and Model 2 of the time and entity fixed models.

model3_fe <- plm(ln_total_vio ~ shall + pm1029+density+avginc+I(avginc^2),data=pmdata, model = "within",index = c("stateid","year"))

model2_fet <- plm(ln_total_vio ~ shall+pm1029 + density+avginc + I(avginc^2),data = pmdata, model = "within", index = c("stateid", "year"), effect = "twoways")

```
> Fe_test <- pFtest(model2_fet, model3_fe)
> print(Fe_test )

        F test for twoways effects

data:  ln_total_vio ~ shall + pm1029 + density + avginc + I(avginc^2)
F = 17.545, df1 = 22, df2 = 1073, p-value < 2.2e-16
alternative hypothesis: significant effects
```

The p-value is 2.2×10^{-16} . Since it is less than 0.05,we can conclude that there's time varying effect. Henceforth, Entity and Time Fixed Effect Model is a better model to interpret the impact of Shall laws on crime.

Since the data is not collected at random. There is no need to build random effects model.

Conclusion

We initially employed a pooled OLS model using log-transformed crime rates and various independent variables. However, the inclusion of the shall law variable yielded an unexpectedly substantial impact on total violence rate, indicating potential omitted variable bias. To address this, we introduced squared terms for variables like incarceration rate, population, and average income, which demonstrated diminishing effects on crime rates

Transitioning to entity fixed effect models revealed a notable reduction in the impact of the shall law variable on total violence rate compared to the pooled OLS model. Acknowledging the limitation of overlooking variable might vary over time but not across economic entities, we introduced a fixed effects and time model accounting for both entity and time-fixed effects. In the entity and time-fixed effects model, the influence of the shall law variable further diminished and lost statistical significance. Only the variable "pm1029" remained significant at the 5% level. In order to build a better model, we eliminated insignificant variables and introduced squared term for average income.

In summary, our examination reveals that the introduction of shall-issue laws does influence crime rates, but the actual impact is notably less than originally predicted.