SHALL YOU

OR

SHALL YOU NOT

DO SHALL-ISSUE LAWS REDUCE CRIME OR NOT?

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Introduction

The history behind shall issue

In 1791, the second amendment to the US constitution was ratified. The amendment read, "A well-regulated militia, being necessary to the security of a free state, the right of the people to keep and bear arms, shall not be infringed". The NRA was formed in 1871.

Assassinations of high profile social figures like President John F. Kennedy, Robert Kennedy & the Rev. Martin Luther King Jr. led to the passage of the Omnibus Crime Control & Safe Streets Act of 1968 & the Gun Control Act of 1968 under President Lyndon B. Johnson. These were the primary federal law regulating firearms. In 1986, Congress passed the Firearm Owners Protection Act of 1986 amid complaints by gun owners of being subjected to harassment.

Findings based on previous studies

One of the first studies that appeared about understanding the effect of right to carry laws on violent crime was done by John Lott & David Mustard which was published in the Journal of Legal Studies. This study was done using data from all 3,054 United States counties & made bold conclusions that right to carry laws deterred violent crime, without increasing accidental deaths & the right to carry concealed handgun laws were "the most cost-effective method of crime thus far analyzed by economists. This paper used cross – sectional time – series county level crime data for the entire US from 1997 to 1992 to investigate the impact of shall issue right to carry firearm laws. Their model made use of county as dummy variables to control for cross county differences & using crime category as an exogeneous variable that is correlated with crimes that are being studied here.

They also stated that, consistent with the notion that criminals respond to incentives, county level data provides evidence that concealed handguns laws are also associated with increases in property crimes involving stealth. The following year another study was published in the same journal which re-analyzed Lott & Mustard's data & concluded that there was no basis for drawing conclusions about impact of right-to-carry laws on violent crime.

A study on the similar subject by Stanford Professor John Donohue found that states that have adopted right-to-carry laws have experienced a 13 to 15 percent increase in violent crime in the 10 years after enacting those laws. Even this report debunked claims that RTC laws had been shown to debunk crime and were not able to definitively conclude their carrying concealed weapons had an effect – positive or negative – on violent crime.

There seem to be enough studies in both the directions & one can always cherry pick a study to support their stand. We intend to use this study and further analyze the impact of shall law in the period pertaining to available data.

Understanding Data

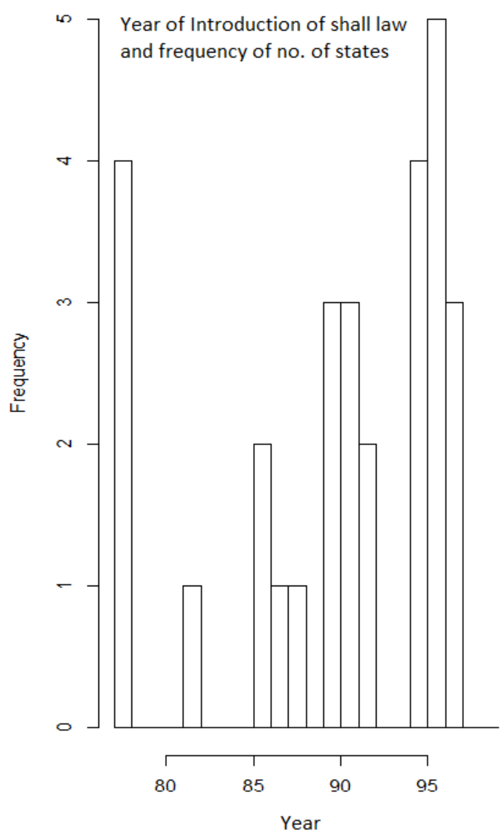
Exploratory Data Analysis

- Data has 1173 observations pertaining to 51 states in the period of 1977 to 1999.
- There is no missing data, so it's a balanced panel data
- Only 29 out of 51 states had shall law effective in the observed period (77 to 99)
    - ID's of the states that implemented shall law are:

```
"2" "4" "5"  "12" "13" "16" "18" "21" "22" "23" "28" "30" "32" "33" "
37" "38" "40" "41" "42" "45" "46" "47" "48" "49" "50" "51" "53" "54"
"56"
```

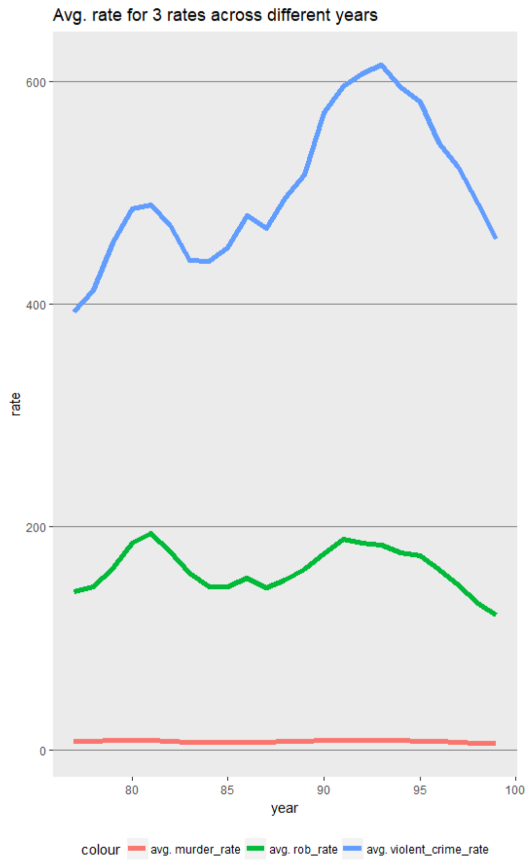
- Data has 3 crime rates, violent rate, robbery rate and murder rate. These crime rates are the dependent variables which can be estimated using available independent variables li ke incarceration rate, density, avg. income, population, percent of state population that i s male and in age 10 to 29, percent of state population that is white and in age 10 to 64 a nd percent of state population that is black and in age 10 to 64

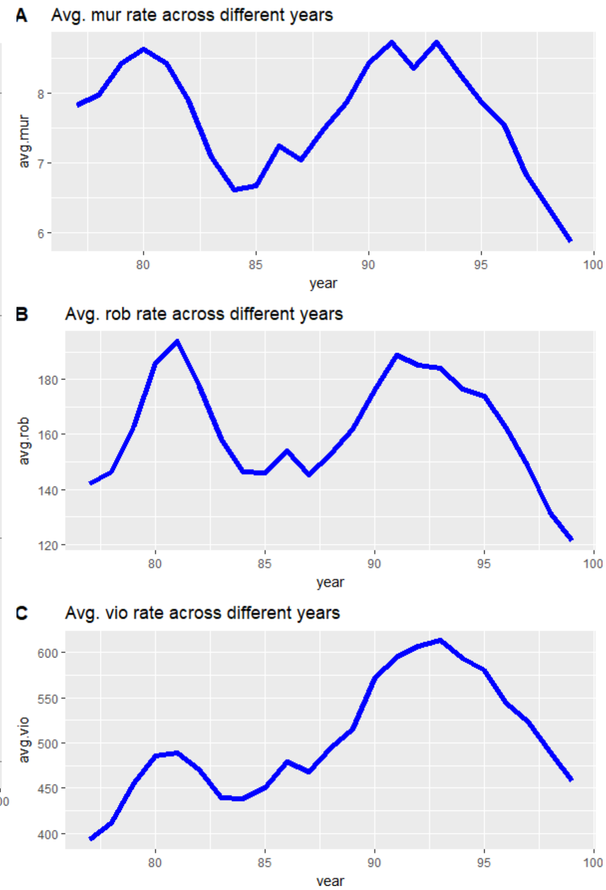
- In the 29 states that had shall law, 4 states had shall law from the start of the observatio n period



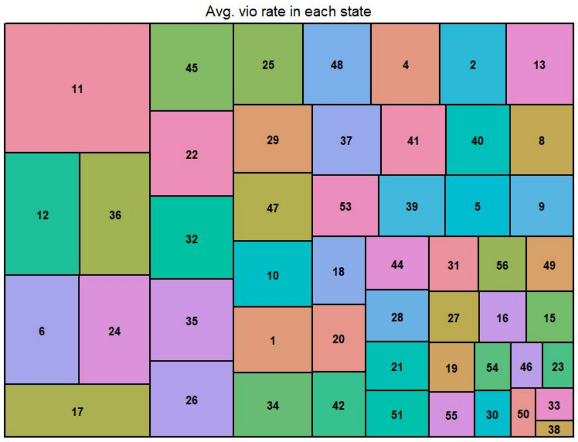
- Average crime rate in all states across different years:
    - As expected violent rate is the highest because it is a combination of diverse types of crime rates
    - Average robbery rate is more than average murder rate

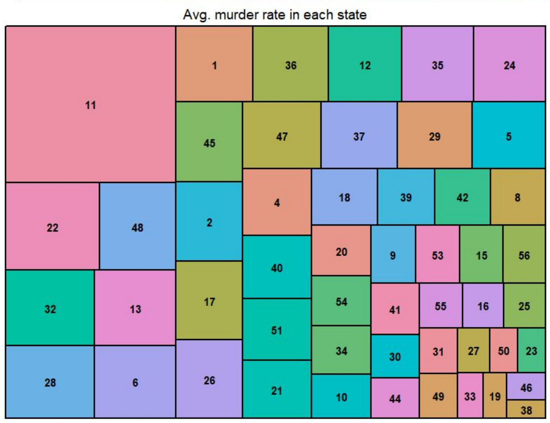
- The trend of all the rates remain the same across the years. All the crime rates have increased in the period of (91-92) and decreased after that

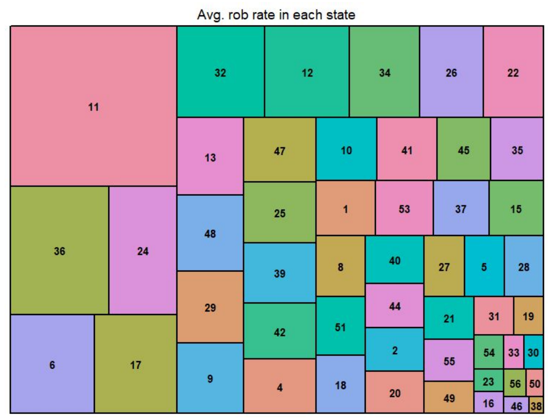




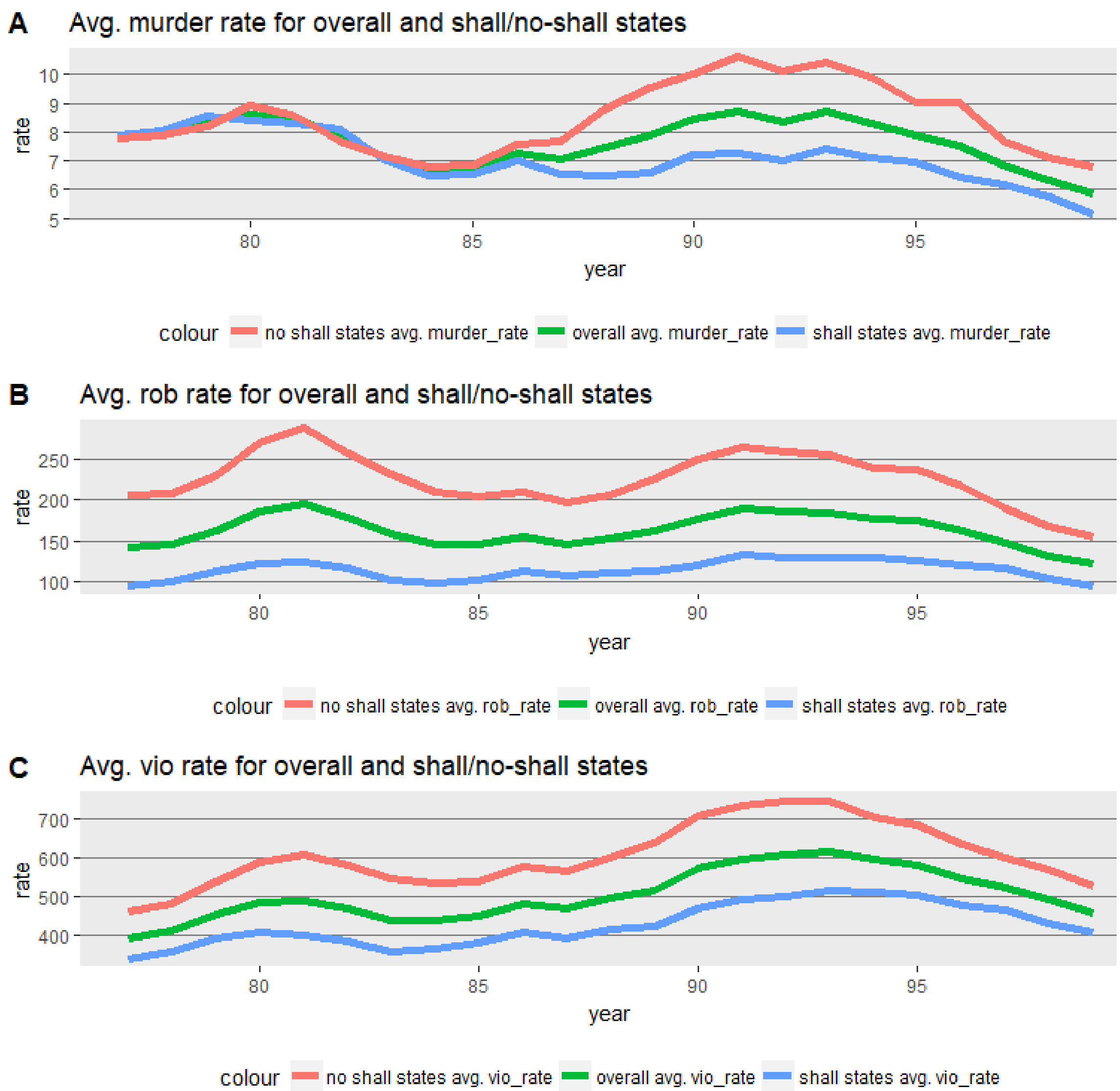
- Average crime rate in all years across different states:
  - State 11 has the highest average violent, murder and robbery rate in all the years and State 38 has the least value





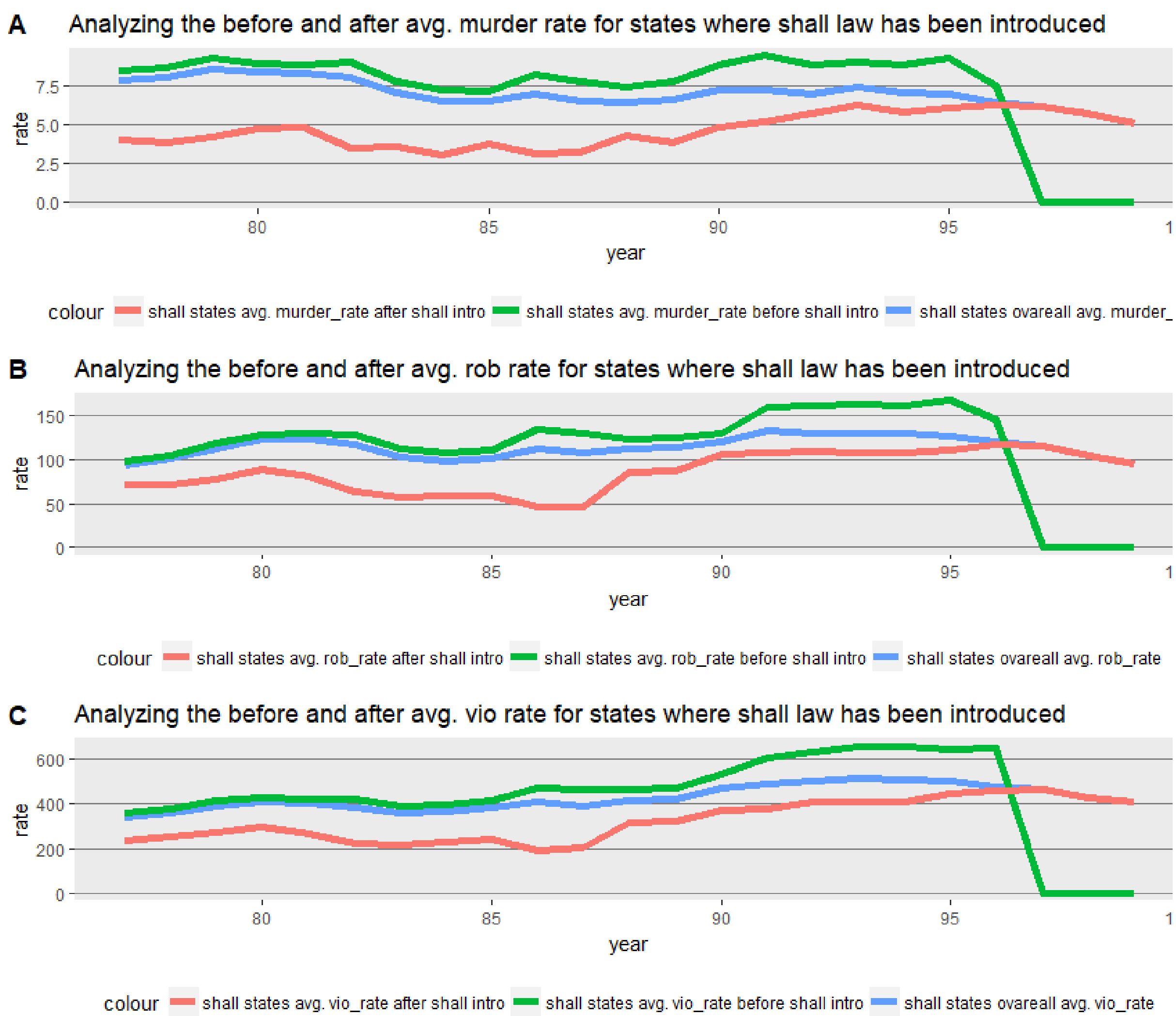


- **Average crime rate in all states across different years for shall and non-shall states:**
  - **Purpose**: Going by the assumption under which shall law has been passed in different states, avg. crime rate should have decreased across years where shall law has been introduced
  - **Understanding graph**: States which have implemented shall law at least once in the observed period are considered as shall states and the rest are non-shall states
  - **Finding:** Trend of avg. crime rate across years in shall and non-shall is analogous with "overall avg. crime rate" and neither an increase nor decrease of avg. crime rate has been observed in shall states
    - **Hypothesis1**: This trend might be because there is no demarcation for avg. crime rate before and after introduction of shall law in shall states
  - **Finding:** Avg. crime rate in States where shall law has been introduced at any given point in time is low when compared to states that never introduced shall law
    - **Conclusion**: This shows that states that adopted shall laws have less avg. murder rate than states that never adopted shall laws



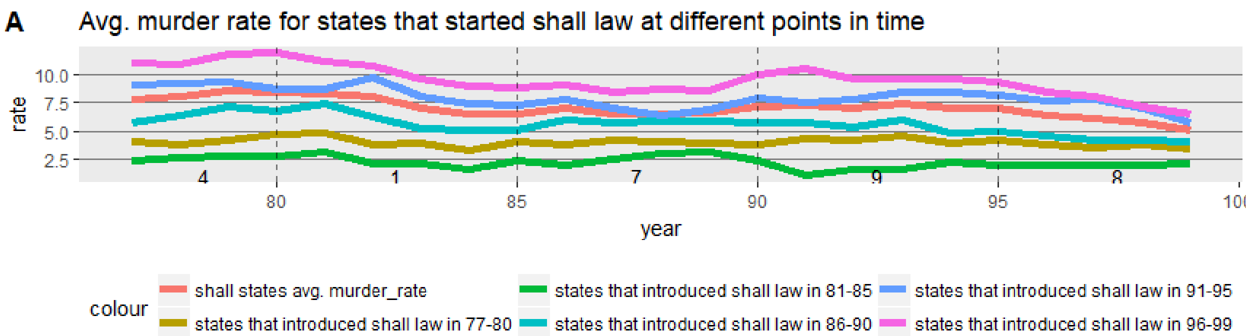
- **Demarcation for avg. crime rate in shall states before and after introduction of shall law across different years**
    - **Purpose:** Effect of shall law couldn't be understood by observing the overall trend of avg. crime rate by shall/non-shall states because more than 50% of states have adopted shall law after 1990, which is at the end of observation period
    - **Understanding the graph:** If shall law has been introduced in state "1" in 1990, then before 1990 state "1" will be accounted to "shall states avg. murder_rate before shall intro" and after 1990 state "1" will be accounted as "shall states avg. murder_rate after shall intro"
    - **Caution:** "shall states avg. murder_rate before shall intro" will be zero for years from 1997 because the last year in which shall law has been implemented (in observed period) is 1997 and there will be no states to "before shall" category because we have taken states that considered only states that implemented shall law

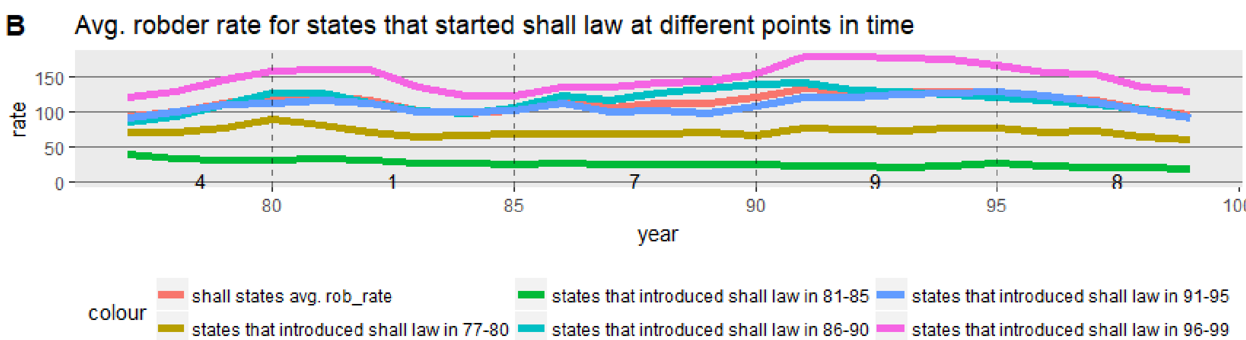
- **Finding:** Trend of "shall states avg. murder_rate before shall intro" is analogus to "shall states overall avg. murder rate"
- **Finding:** Trend of "shall states avg. murder_rate after shall intro" has increased over years.
  - **Hypothesis:** While this shows that shall law has not been effective in controlling crime rate, this also might be because the states that have adopted shall laws in initial period of the observation have less avg. murder rate than states that implemented shall laws in the later part of the period of observation period (which has also been concluded from above graph that “states that adopted shall laws have less avg. murder rate than states that never adopted shall laws”)

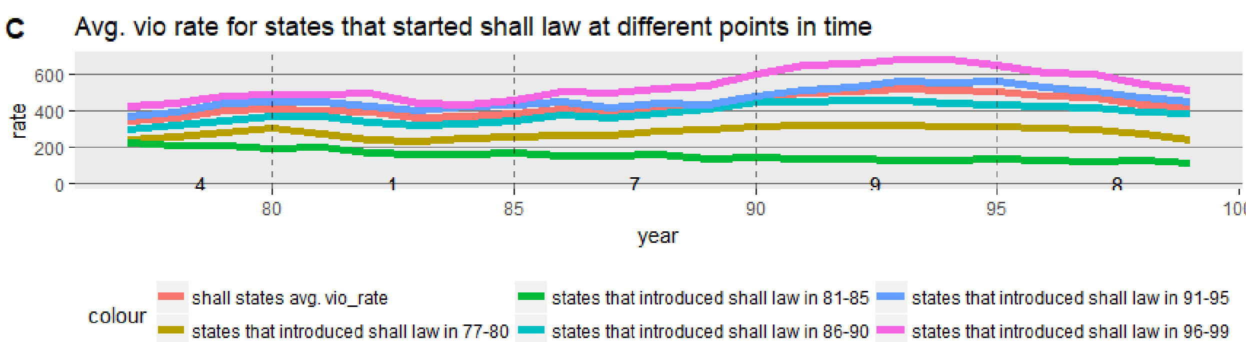


- **Average crime rate in shall states split by different time periods during which they have introduced shall law**

- **Purpose:** States that have adopted shall laws in initial period of the observation have less avg. murder rate than states that implemented shall laws in the later part of the period of observation period
- **Understanding graph:** For states in which shall law has been introduced, data has been split into several bins based on year of introduction of shall law and each bin has 5 years
- **Finding:** States that have introduced shall law in (77-80), (81-85), (86-90) have less average crime rate than states that have introduced shall law in (91-95), (96-100)



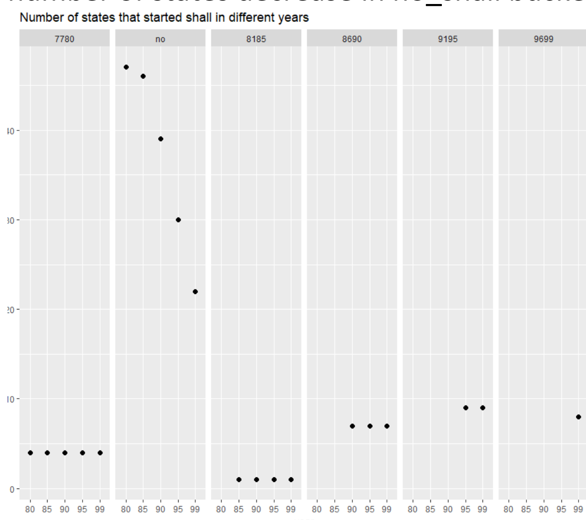




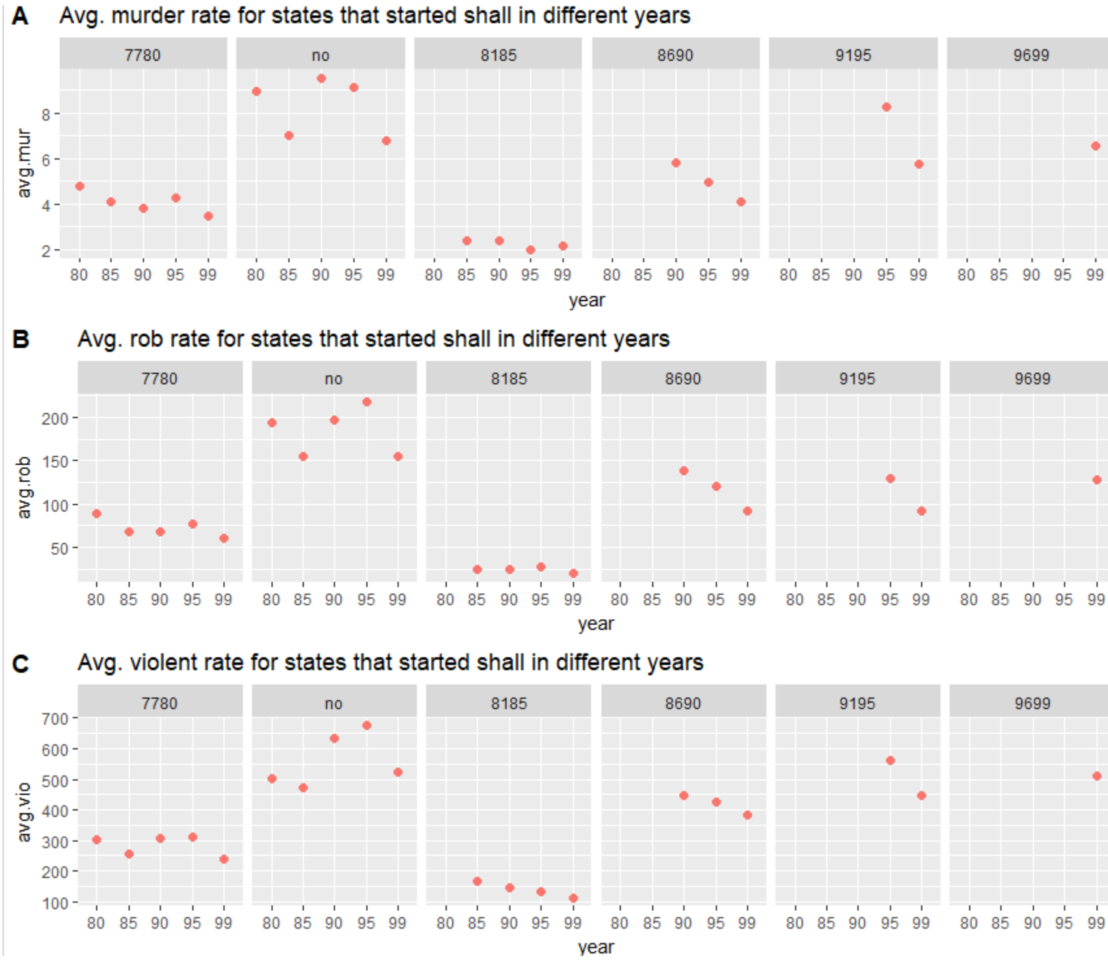
- **Average crime rate in all states across different years for non-shall states and split by bin of year of introduction of law in shall states**
  - **Purpose**: Going by the assumption under which shall law has been passed in different states, avg. crime rate should have decreased across years where shall law has been introduced and decrease of avg. crime rate also varies depending on

the year of introduction of shall law (because we have only limited observation period and more than 50% of the states have implemented shall law in the later period of observation)

- **Understanding graph:** States that never adopted shall law and states that adopted shall law in the initial period of observation and in the final period of observation. Suppose if 4 states have implemented shall law in 77-80 period, then avg. crime rate of these states is observed till the end of observation period.
- **Caution:** While the number of states remains the same for shall_year buckets, the number of states decrease in no_shall bucket over years

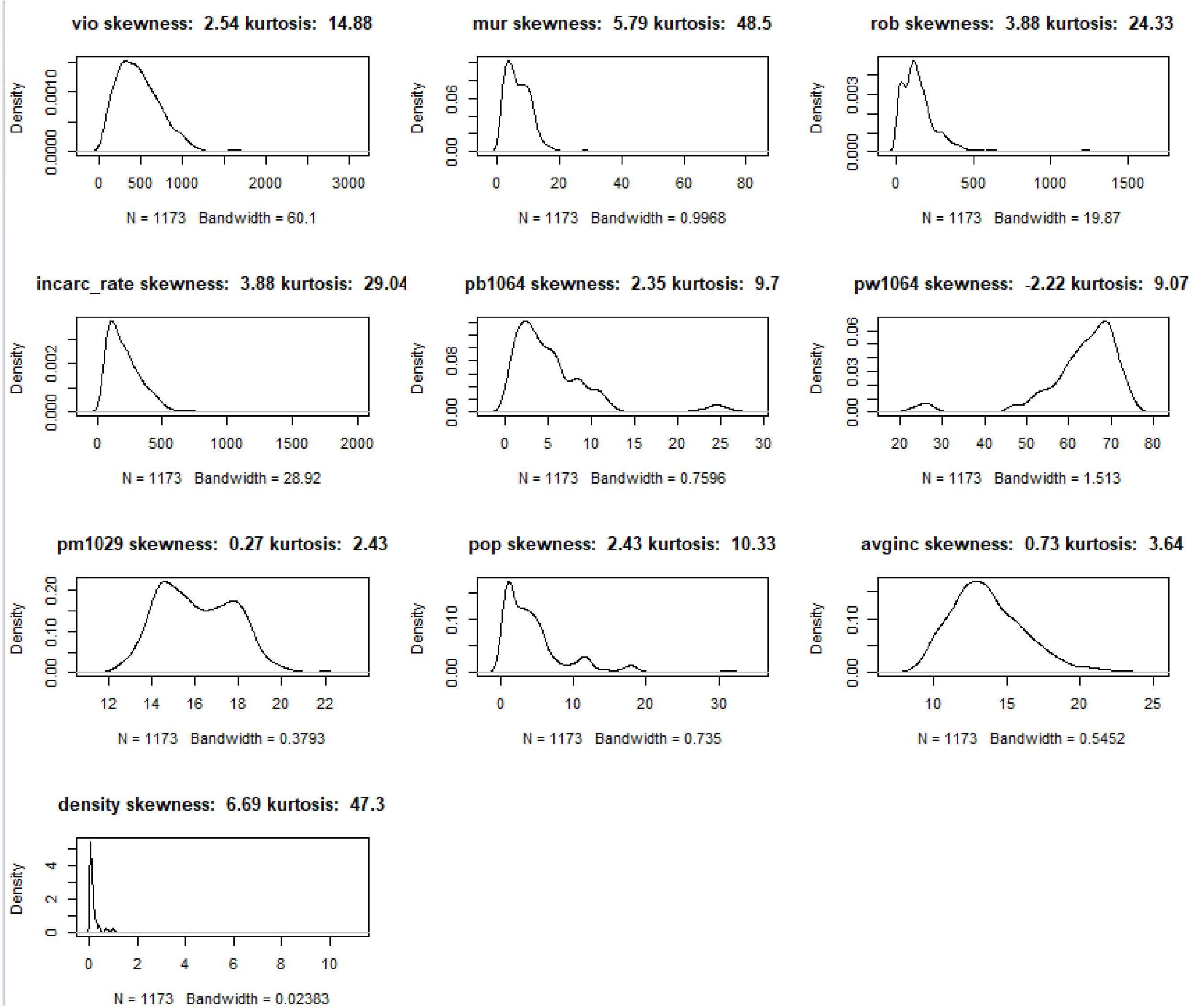


- **Finding:** In states where shall law has been implemented across different time periods, avg. crime rate has observed to be decreased after shall law introduction. Though a decrease has been observed, it seems to be less showing that shall law has been effective but not a very significant effect in decreasing crime rate.

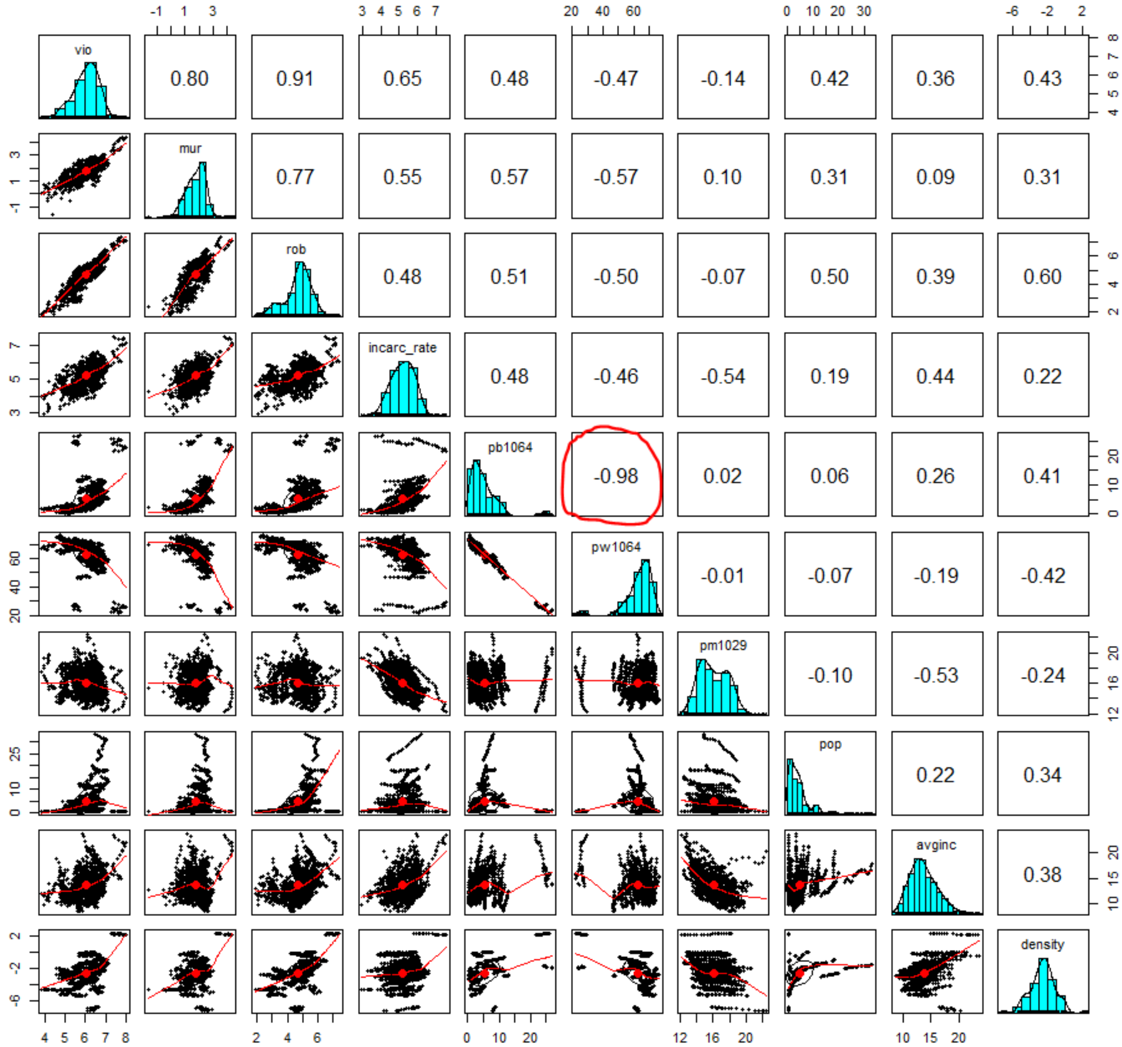


Assumptions of linear regression

- **Checking skewness of the variables:**
  - Vio, mur, rob, incar_rate, density are highly skewed



- **Transforming the variables:**
  - Log transformation for vio, mur, rob, incar_rate and density
- **Pairwise Correlation – post data transformation**
  - High correlation has been observed for mur, vio and rob. This is not relevant because none of the variables form a dependent-independent pair
  - pw1064 and pb1064 are highly correlated (-0.98)



- **Auxiliary Model for all independent variable – post data transformation**
  - R-Square is high for pb1064 and pw1064, which might because of the identified pairwise correlation

```
var          rsquare
incarc_rate  0.578190274932209
pb1064       0.976166187760185
pw1064       0.974992604093382
pm1029       0.623960984247605
pop          0.193754128667703
avginc       0.555869100580109
density      0.406198629825855
shall        0.202172002208727
```

  - Removing either one of the variables leads to R-Square for all the variables less than 80%
    - Excluding pw1064

var	rsquare
incarc_rate	0.576888980132899
pb1064	0.509033127629233
pm1029	0.586093700441132
pop	0.190218257714515
avginc	0.394976288945955
density	0.388935775280793
shall	0.153083714022091

- Excluding pb1064

var	rsquare
incarc_rate	0.5631681422277
pw1064	0.484857779742881
pm1029	0.555565321625998
pop	0.182688831855132
avginc	0.380920780014331
density	0.403407982613985
shall	0.159692682800535

Estimated impact of independent variables

The below mentioned relationships are based on basic intuition, pervious research work. These relationships might be valid or not valid for our data and regression models can help us understand that.

- **Density:** Densely populated states have high crime rate
- **Incarceration Rate:** states with the biggest jumps in incarceration levels have not shown corresponding drops in crime, compared to states with smaller increases in their population behind bars. (http://abcnews.go.com/US/story?id=95580) This might lead to simultaneous-causality bias.
- **Population:** Chance of committing crime in highly populated states is higher
- **Pm1029:** People in the 15-24 age range account for about 40 percent of all arrests even though they comprise only about 14 percent of the population. (https://2012books.lardbucket.org/books/a-primer-on-social-problems/s11-03-who-commits-crime.html)
- **Pw1064 and Pb1064:** In violent/aggressive crimes, blacks commit them at a rate many times higher than their representative population, while whites tend to commit them at a rate markedly lower than their representative population. #(https://infogram.com/us-crime-in-black-and-white-1gzxop49q0okmwy)
- **Shall:** There seem to be enough studies in both the directions & one can always cherry pick a study to support their stand. From the Exploratory Data Analysis it has been observed that, that shall law has been effective but not a very significant effect in decreasing crime rate

Pooled Regression Models

Murder Rate

Pooled Regression model

To begin with, we chose a Pooled regression model (Simple OLS on panel data) to understand impact of various features on murder rate.

Pooled without cluster robust S.E

```
> summary(mur_polled)
Pooling Model

Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall + pw1064, data = guns_mur2
    model = "pooling")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.118146 -0.253788  0.028293  0.287655  1.180116

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
(Intercept)      -4.7026756  0.5516233 -8.5252 < 2.2e-16 ***
log(incarc_rate)  0.7362824  0.0283905 25.9341 < 2.2e-16 ***
pb1064            0.0398446  0.0161883  2.4613   0.01399 *
pm1029            0.1661738  0.0114954 14.4557 < 2.2e-16 ***
pop               0.0228870  0.0025891  8.8396 < 2.2e-16 ***
avginc           -0.0420935  0.0071722 -5.8690 5.712e-09 ***
log(density)      0.0752280  0.0100841  7.4600 1.687e-13 ***
shall1           -0.2172423  0.0318605 -6.8185 1.474e-11 ***
pw1064            0.0076499  0.0079099  0.9671   0.33368
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    579.9
Residual Sum of Squares: 203.39
R-Squared:      0.64927
Adj. R-Squared: 0.64686
F-statistic: 269.349 on 8 and 1164 DF, p-value: < 2.22e-16
```

We have observed that “pw1064” is insignificant and it might be because of high correlation with “pb1064”, which has been observed earlier. Therefore, removing “pw1064” and executing pooled model.

Pooled without cluster robust S.E without “pw1064”

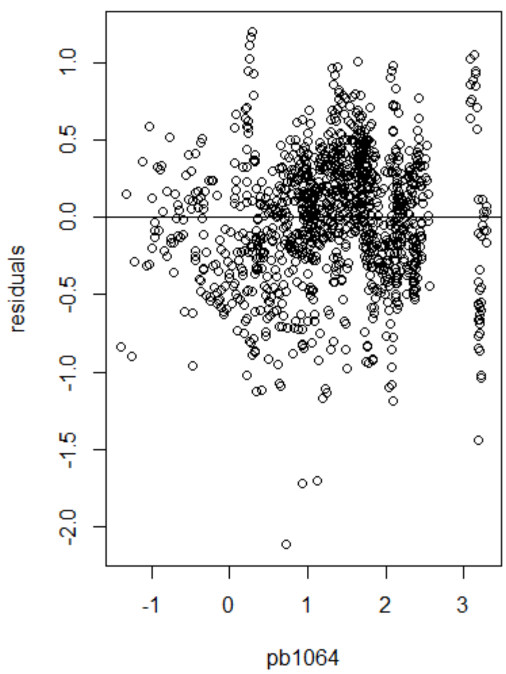
```
> summary(mur_polled3)
Pooling Model

Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall, data = guns_mur2, model = "pooling")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.121113 -0.256808  0.029696  0.284018  1.201426

Coefficients:
                  Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)      -4.2559318  0.3015031 -14.1157 < 2.2e-16 ***
log(incarc_rate)  0.7378051  0.0283461  26.0285 < 2.2e-16 ***
pb1064            0.0245733  0.0035666   6.8898 9.128e-12 ***
pm1029            0.1695364  0.0109566  15.4734 < 2.2e-16 ***
pop               0.0227215  0.0025834   8.7952 < 2.2e-16 ***
avginc           -0.0385165  0.0061449  -6.2681 5.137e-10 ***
log(density)      0.0735888  0.0099404   7.4030 2.544e-13 ***
shall1           -0.2098240  0.0309225  -6.7855 1.837e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    579.9
Residual Sum of Squares: 203.55
R-Squared:      0.64899
Adj. R-Squared: 0.64688
F-statistic: 307.711 on 7 and 1165 DF, p-value: < 2.22e-16
```

Now all the variables are significant.

Log(incarceration_rate), pb1064, pm1029, pop, log(density) impact the murder_rate positively and avg_income, shall law impacts murder_rate negatively. This shows that shall law has decreased murder rate.

Checking for heteroskedasticity using plots

Plot between pb1064 and residuals is cone shaped and higher values of pb1064 have high residuals. This shows that heteroskedasticity is present and we can correct for it using cluster robust standard errors. If we use our pooled OLS model neglecting this effect of heteroscedasticity, the OLS estimates of the model are still unbiased and linear but no longer the best and the standard errors are incorrect which makes the confidence intervals and hypothesis tests misleading.



Pooled with cluster robust S.E without "pw1064"

```
> coeftest(mur_polled3, vcov=vcovHC(mur_polled3,type="HC0",cluster="group"))

t test of coefficients:

                  Estimate Std. Error t value  Pr(>|t|)
(Intercept)     -4.2559318  1.3629535 -3.1226  0.001837 **
log(incarc_rate)  0.7378051  0.1290084  5.7190 1.360e-08 ***
pb1064           0.0245733  0.0190735  1.2883  0.197881
pm1029           0.1695364  0.0425900  3.9807 7.297e-05 ***
pop              0.0227215  0.0086313  2.6325  0.008589 **
avginc          -0.0385165  0.0229772 -1.6763  0.093950 .
log(density)     0.0735888  0.0403299  1.8247  0.068307 .
shall1          -0.2098240  0.0747732 -2.8061  0.005097 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Only "pb1064" becomes insignificant at p value of 0.1

Using the robust standard errors, we corrected the OLS standard errors but these estimates are still not the best as the model is inefficient. This could be because of the omitted variable bias. So, we next wanted to implement a fixed effects model which is immune to omitted variable bias from variables that are constant over time and vary between states and not within states. For example, the cultural attitude of the people committing crime cannot be quantified using a pooled OLS model where as it won't introduce any bias in a fixed effects model.

Fixed Effects – Entity fixed model

Entity Fixed model without cluster robust SE

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall, data = guns_mur2, model = "within")

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

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.7015e+00 -1.2142e-01  5.7961e-05  1.2725e-01  8.3474e-01

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.1396703  0.0376487 -3.7098 0.0002176 ***
pb1064           -0.0474174  0.0169420 -2.7988 0.0052175 **
pm1029            0.0098599  0.0110683  0.8908 0.3732177
pop              -0.0131893  0.0126114 -1.0458 0.2958687
avginc            0.0388111  0.0078831  4.9233 9.792e-07 ***
log(density)     -0.3758613  0.1184775 -3.1724 0.0015530 **
shall            -0.0367866  0.0242786 -1.5152 0.1300087
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 54.341
R-Squared:      0.14172
Adj. R-Squared: 0.097839
F-statistic: 26.3005 on 7 and 1115 DF, p-value: < 2.22e-16
```

Pm1029 and pop are insignificant. Using F-test to check for the relevance of these variables combined.

Combined F-test

```
Linear hypothesis test

Hypothesis:
pop = 0
pm1029 = 0

Model 1: restricted model
Model 2: log(mur) ~ log(incarc_rate) + pb1064 + pm1029 + pop + avginc +
    log(density) + shall

  Res.Df Df  Chisq Pr(>Chisq)
1   1117
2   1115  2 1.6972      0.428
```

This shows that both the variables pm1029 and pop are insignificant.

Entity Fixed model without pm1029 and pop & without cluster Robust SE

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + avginc +
    log(density) + shall, data = guns_mur2, model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.7093076 -0.1201162 -0.0010263  0.1277472  0.8311110

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.1629065  0.0280028 -5.8175 7.794e-09 ***
pb1064           -0.0507060  0.0166477 -3.0458  0.002375 **
avginc            0.0368018  0.0075254  4.8903 1.154e-06 ***
log(density)     -0.4545260  0.1018125 -4.4643 8.845e-06 ***
shall1           -0.0354431  0.0242527 -1.4614  0.144185
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 54.424
R-Squared:      0.14041
Adj. R-Squared: 0.098084
F-statistic: 36.4911 on 5 and 1117 DF, p-value: < 2.22e-16
```

Now all the variables are significant except shall at p-value of 0.1. Shall is significant at p-value of 0.15.

After controlling for entity fixed effects, the direction of impact of log(incarceration_rate), pb1064, avginc and log(density) have changed in comparison to pooled model. Controlling for omitted variables bias has lead to this change.

Interpretations

- One percent increase in incarceration_rate leads to decrease of murder_rate by 16%.
- A unit increase in pb1064 leads to 5% drop in murder_rate
- A unit increase in average income leads to 3% increase in murdedr_rate
- One percent increase in density leads to decrease of murder_rate by 45%
- Having shall law leads to decrease of murder rate by 3% compared to not having shall law

We are not planning to use Cluster Robust Standard errors for Entity Fixed effects because fixed effects controls for omitted variable bias because of variables that are constant over time and change with states.

Still there can be omitted variables which can possibly vary over time but are constant across states. We then implemented used entity fixed and time fixed effects model to address the bias from such omitted variables.

Fixed Effects with time & entity fixed effects without cluster Robust SE

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall + factor(year) - 1, data = guns_mur2,
    model = "within")

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

Residuals:
      Min.     1st Qu.      Median     3rd Qu.        Max.
-1.74821883 -0.10225198 -0.00038501  0.10895271  0.86636255

Coefficients: (1 dropped because of singularities)
                   Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.0908782  0.0411052 -2.2109 0.0272513 *
pb1064           -0.0489249  0.0164433 -2.9754 0.0029907 **
pm1029            0.0557285  0.0164421  3.3894 0.0007255 ***
pop              -0.0182566  0.0117357 -1.5556 0.1200817
avginc            0.0684971  0.0088808  7.7129 2.757e-14 ***
log(density)     -0.2575324  0.1120850 -2.2977 0.0217698 *
shall0            0.0206236  0.0254173  0.8114 0.4173137
factor(year)78    0.0021053  0.0410139  0.0513 0.9590700
factor(year)79    0.0749089  0.0415343  1.8035 0.0715785 .
factor(year)80    0.1240038  0.0419811  2.9538 0.0032060 **
factor(year)81    0.1397256  0.0428939  3.2575 0.0011587 **
factor(year)82    0.0717179  0.0452719  1.5842 0.1134467
factor(year)83    0.0236595  0.0486384  0.4864 0.6267555
factor(year)84   -0.0849153  0.0525969 -1.6145 0.1067176
factor(year)85   -0.0369335  0.0566491 -0.6520 0.5145573
factor(year)86    0.0368564  0.0616945  0.5974 0.5503627
factor(year)87    0.0210620  0.0666397  0.3161 0.7520187
factor(year)88    0.0339747  0.0718724  0.4727 0.6365156
factor(year)89    0.0391858  0.0768662  0.5098 0.6103000
factor(year)90    0.1224525  0.0821345  1.4909 0.1362823
factor(year)91    0.1772175  0.0862327  2.0551 0.0401057 *
factor(year)92    0.1448846  0.0909132  1.5937 0.1113016
factor(year)93    0.2375319  0.0941691  2.5224 0.0117969 *
factor(year)94    0.1310367  0.0979142  1.3383 0.1810832
factor(year)95    0.1500480  0.1019824  1.4713 0.1414944
factor(year)96    0.0864888  0.1060023  0.8159 0.4147271
factor(year)97   -0.0148486  0.1096548 -0.1354 0.8923112
factor(year)98   -0.0766863  0.1136346 -0.6748 0.4999139
factor(year)99   -0.1423148  0.1166431 -1.2201 0.2226951
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 45.997
R-Squared:      0.27351
Adj. R-Squared: 0.221
F-statistic: 14.1897 on 29 and 1093 DF, p-value: < 2.22e-16
```

Shall variable is insignificant though the joint effects of time are statistically significant.

```
Linear hypothesis test

Hypothesis:
factor(year)78 = 0
factor(year)79 = 0
factor(year)80 = 0
factor(year)81 = 0
factor(year)82 = 0
factor(year)83 = 0
factor(year)84 = 0
factor(year)85 = 0
factor(year)86 = 0
factor(year)87 = 0
factor(year)88 = 0
factor(year)89 = 0
factor(year)90 = 0
factor(year)91 = 0
factor(year)92 = 0
factor(year)93 = 0
factor(year)94 = 0
factor(year)95 = 0
factor(year)96 = 0
factor(year)97 = 0
factor(year)98 = 0
factor(year)99 = 0

Model 1: restricted model
Model 2: log(mur) ~ log(incarc_rate) + pb1064 + pm1029 + pop + avginc +
    log(density) + shall + factor(year) - 1

  Res.Df Df  Chisq Pr(>Chisq)
1   1115
2   1093 22 198.29  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

We further wanted to address any bias from unobserved omitted variables. So, we decided to try and implement Random effects model. But we saw that the data is not collected using random sampling. So, we should not implement Random effects model.

This leaves us with Fixed effects model with entity fixed effects as our best model for understanding impact of shall law on murder rate.

Violence Rate

To understand the impact of the independent variables on violence rate, we chose a Pooled regression model (Simple OLS on panel data) to understand the impact.

Pooled without Cluster Robust SE

```
Pooling Model

Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall + pw1064, data = guns_mur2,
    model = "pooling")

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

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
-1.2400 -0.2370  0.0116  0.2580  1.1000

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)       0.1816538  0.4902108  0.3706 0.7110307
log(incarc_rate)  0.6935672  0.0252298 27.4900 < 2.2e-16 ***
pb1064            0.0033125  0.0143860  0.2303 0.8179308
pm1029            0.1167641  0.0102156 11.4300 < 2.2e-16 ***
pop               0.0240749  0.0023009 10.4633 < 2.2e-16 ***
avginc            0.0232989  0.0063738  3.6554 0.0002682 ***
log(density)      0.0928883  0.0089614 10.3653 < 2.2e-16 ***
shall1           -0.2826839  0.0283135 -9.9841 < 2.2e-16 ***
pw1064            0.0033576  0.0070293  0.4777 0.6329816
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 160.62
R-Squared:      0.67128
Adj. R-Squared: 0.66902
F-statistic: 297.126 on 8 and 1164 DF, p-value: < 2.22e-16
```

We once again observe that “pw1064” is insignificant and it might be because of high correlation with “pb1064”, which has been observed earlier. Therefore, removing “pw1064” and executing pooled model.

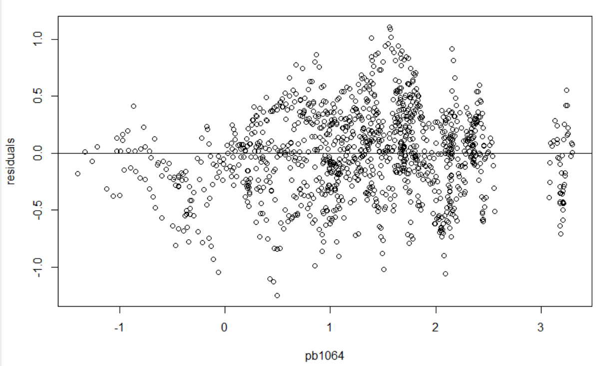
Pooled without cluster robust S.E without “pw1064”

```
Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall, data = guns_mur2, model = "pooling")

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

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
 -1.250  -0.236   0.012   0.258   1.110

Coefficients:
                   Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)       0.3777348  0.2678552   1.4102    0.1587
log(incarc_rate)  0.6942355  0.0251826  27.5680 < 2.2e-16 ***
pb1064           -0.0033903  0.0031686  -1.0700    0.2849
pm1029            0.1182400  0.0097339  12.1473 < 2.2e-16 ***
pop               0.0240022  0.0022951  10.4580 < 2.2e-16 ***
avginc            0.0248689  0.0054591   4.5555 5.776e-06 ***
log(density)      0.0921688  0.0088310  10.4369 < 2.2e-16 ***
shall1           -0.2794280  0.0274716 -10.1715 < 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: 160.65
R-Squared:      0.67122
Adj. R-Squared: 0.66924
F-statistic: 339.765 on 7 and 1165 DF, p-value: < 2.22e-16
```

Now we notice that all the variables are significant except for pb1064.

Log(incarceration_rate), pm1029, pop, log(density) impact the violence_rate positively and avg_income, pb1064 & shall_law impacts violence_rate negatively. We can say that shall law has decreased violence rate.

Plots for heteroskedasticity:



Plot between pb1064 and residuals is cone shaped and higher values of pb1064 have high residuals. This shows that heteroskedasticity is present and we can correct for it using cluster robust standard errors. If we use our pooled OLS model neglecting this effect of heteroscedasticity, the OLS estimates of the model are still unbiased and linear but no longer the best and the standard errors are incorrect which makes the confidence intervals and hypothesis tests misleading.

Pooled with cluster robust S.E without "pw1064"

```
t test of coefficients:

                  Estimate Std. Error t value  Pr(>|t|)    
(Intercept)      0.3777348  0.8818111  0.4284 0.6684664    
log(incarc_rate)  0.6942355  0.0912229  7.6103 5.622e-14 ***
pb1064          -0.0033903  0.0118007 -0.2873 0.7739385    
pm1029           0.1182400  0.0288696  4.0957 4.501e-05 ***
pop              0.0240022  0.0074262  3.2321 0.0012632 ** 
avginc           0.0248689  0.0164515  1.5117 0.1308937    
log(density)     0.0921688  0.0332417  2.7727 0.0056482 ** 
shall1          -0.2794280  0.0779221 -3.5860 0.0003497 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We notice that pb1064 is highly insignificant. But, we do know that using the robust standard errors, we corrected the OLS standard errors, but these estimates are still not the best as the model is inefficient. This could be because of the omitted variable bias. So, we next wanted to implement a fixed effects model which is immune to omitted variable bias from variables that are constant over time and vary between states and not within states. For example, the cultural attitude of the people committing crime cannot be quantified using a pooled OLS model where as it won't introduce any bias in a fixed effects model.

Fixed Effects – Entity fixed model

Entity Fixed model without cluster robust SE

```
Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pm1029 + 
    pop + avginc + log(density) + shall, data = guns_mur2, model = "within")

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

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max. 
-0.58300 -0.10500  0.00718  0.10600  0.56200 

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)    
log(incarc_rate) -0.0090546  0.0281105 -0.3221  0.747433    
pb1064            0.0241139  0.0126498  1.9063  0.056871 .  
pm1029           -0.0512862  0.0082642 -6.2058 7.658e-10 ***
pop               0.0114121  0.0094163  1.2119  0.225790    
avginc           -0.0014284  0.0058860 -0.2427  0.808303    
log(density)     -0.2671710  0.0884615 -3.0202  0.002584 ** 
shall1            0.0204939  0.0181277  1.1305  0.258495    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 30.295
R-Squared:      0.17653
Adj. R-Squared: 0.13443
F-statistic: 34.1455 on 7 and 1115 DF, p-value: < 2.22e-16
```

We notice that log(incarc_rate), pop & avginc become insignificant after entity fixed model is used.

Using F-test to check for the relevance of these variables combined.

Combined F-test

```
Linear hypothesis test

Hypothesis:
log(incarc_rate) = 0
avginc = 0
pop = 0

Model 1: restricted model
Model 2: log(vio) ~ log(incarc_rate) + pb1064 + pm1029 + pop + avginc + 
    log(density) + shall

  Res.Df Df  Chisq Pr(>Chisq)
1   1118                     
2   1115  3 1.5916     0.6613
```

This shows that log(incarc_rate), avginc & pop are insignificant & we continue our regression by dropping the variables.

Entity Fixed model without log(incarc_rate), avginc, pop & without cluster Robust SE

```
Call:
plm(formula = log(vio) ~ pb1064 + pm1029 + log(density) + shall,
    data = guns_mur2, model = "within")

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

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-0.58700 -0.10600  0.00699  0.10500  0.55600

Coefficients:
              Estimate Std. Error  t-value  Pr(>|t|)
pb1064       0.0260712  0.0121671   2.1428  0.032347 *
pm1029      -0.0478386  0.0044686 -10.7056 < 2.2e-16 ***
log(density) -0.2190227  0.0795102  -2.7547  0.005971 **
shall1       0.0188139  0.0179096   1.0505  0.293717
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Now all the variables are significant except shall at p-value of 0.1. Shall is significant at p-value of 0.29.

After controlling for entity fixed effects, the direction of impact of log(density) & pm1029 have changed in comparison to pooled model. We believe, controlling for omitted variables bias has led to this change.

Interpretations:

- One percent increase in incarceration_rate leads to decrease of murder_rate by 16%.
- A unit increase in pb1064 leads to 2% increase in violence_rate
- A unit increase in pm1029 income leads to a drop of 5% in violence_rate
- One percent increase in density leads to decrease of murder_rate by 21%
- Having shall law leads to increase in the violence rate by 2% compared to not having shall law

We are not planning to use Cluster Robust Standard errors for Entity Fixed effects because fixed effects controls for omitted variable bias because of variables that are constant over time and change with states.

Still there can be omitted variables which can possibly vary over time but are constant across states. We then implemented used entity fixed and time fixed effects model to address the bias from such omitted variables.

Fixed Effects with time & entity fixed effects without cluster Robust SE

```
Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.1035180  0.0278617 -3.7154 0.0002131 ***
pb1064           -0.0089000  0.0111455 -0.7985 0.4247401
pm1029            0.0772543  0.0111447  6.9319 7.084e-12 ***
pop               0.0064205  0.0079546  0.8071 0.4197606
avginc            0.0021565  0.0060196  0.3583 0.7202254
log(density)     -0.2520221  0.0759730 -3.3173 0.0009390 ***
shall0            0.0282769  0.0172283  1.6413 0.1010209
factor(year)78    0.0671185  0.0277998  2.4144 0.0159268 *
factor(year)79    0.1856235  0.0281526  6.5935 6.674e-11 ***
factor(year)80    0.2474713  0.0284554  8.6968 < 2.2e-16 ***
factor(year)81    0.2553967  0.0290742  8.7843 < 2.2e-16 ***
factor(year)82    0.2485782  0.0306860  8.1007 1.450e-15 ***
factor(year)83    0.2268472  0.0329679  6.8809 1.000e-11 ***
factor(year)84    0.2685999  0.0356510  7.5341 1.028e-13 ***
factor(year)85    0.3267886  0.0383976  8.5107 < 2.2e-16 ***
factor(year)86    0.4145253  0.0418174  9.9127 < 2.2e-16 ***
factor(year)87    0.4230712  0.0451694  9.3663 < 2.2e-16 ***
factor(year)88    0.4943054  0.0487162 10.1466 < 2.2e-16 ***
factor(year)89    0.5590499  0.0521011 10.7301 < 2.2e-16 ***
factor(year)90    0.6927999  0.0556720 12.4443 < 2.2e-16 ***
factor(year)91    0.7569464  0.0584498 12.9504 < 2.2e-16 ***
factor(year)92    0.7993340  0.0616223 12.9715 < 2.2e-16 ***
factor(year)93    0.8311131  0.0638293 13.0209 < 2.2e-16 ***
factor(year)94    0.8268422  0.0663677 12.4585 < 2.2e-16 ***
factor(year)95    0.8323324  0.0691252 12.0409 < 2.2e-16 ***
factor(year)96    0.7876731  0.0718500 10.9627 < 2.2e-16 ***
factor(year)97    0.7765270  0.0743257 10.4476 < 2.2e-16 ***
factor(year)98    0.7308377  0.0770233  9.4885 < 2.2e-16 ***
factor(year)99    0.6808562  0.0790625  8.6116 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.132
R-Squared:      0.42558
Adj. R-Squared: 0.38406
F-statistic: 27.9233 on 29 and 1093 DF, p-value: < 2.22e-16
```

Shall variable is insignificant though the joint effects of time are statistically significant.


```
Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.1035180  0.0278617 -3.7154 0.0002131 ***
pb1064           -0.0089000  0.0111455 -0.7985 0.4247401
pm1029            0.0772543  0.0111447  6.9319 7.084e-12 ***
pop               0.0064205  0.0079546  0.8071 0.4197606
avginc            0.0021565  0.0060196  0.3583 0.7202254
log(density)     -0.2520221  0.0759730 -3.3173 0.0009390 ***
shall0            0.0282769  0.0172283  1.6413 0.1010209
factor(year)78    0.0671185  0.0277998  2.4144 0.0159268 *
factor(year)79    0.1856235  0.0281526  6.5935 6.674e-11 ***
factor(year)80    0.2474713  0.0284554  8.6968 < 2.2e-16 ***
factor(year)81    0.2553967  0.0290742  8.7843 < 2.2e-16 ***
factor(year)82    0.2485782  0.0306860  8.1007 1.450e-15 ***
factor(year)83    0.2268472  0.0329679  6.8809 1.000e-11 ***
factor(year)84    0.2685999  0.0356510  7.5341 1.028e-13 ***
factor(year)85    0.3267886  0.0383976  8.5107 < 2.2e-16 ***
factor(year)86    0.4145253  0.0418174  9.9127 < 2.2e-16 ***
factor(year)87    0.4230712  0.0451694  9.3663 < 2.2e-16 ***
factor(year)88    0.4943054  0.0487162 10.1466 < 2.2e-16 ***
factor(year)89    0.5590499  0.0521011 10.7301 < 2.2e-16 ***
factor(year)90    0.6927999  0.0556720 12.4443 < 2.2e-16 ***
factor(year)91    0.7569464  0.0584498 12.9504 < 2.2e-16 ***
factor(year)92    0.7993340  0.0616223 12.9715 < 2.2e-16 ***
factor(year)93    0.8311131  0.0638293 13.0209 < 2.2e-16 ***
factor(year)94    0.8268422  0.0663677 12.4585 < 2.2e-16 ***
factor(year)95    0.8323324  0.0691252 12.0409 < 2.2e-16 ***
factor(year)96    0.7876731  0.0718500 10.9627 < 2.2e-16 ***
factor(year)97    0.7765270  0.0743257 10.4476 < 2.2e-16 ***
factor(year)98    0.7308377  0.0770233  9.4885 < 2.2e-16 ***
factor(year)99    0.6808562  0.0790625  8.6116 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.132
R-Squared:      0.42558
Adj. R-Squared: 0.38406
F-statistic: 27.9233 on 29 and 1093 DF, p-value: < 2.22e-16
```


We further wanted to address any bias from unobserved omitted variables. So, we decided to try and implement Random effects model. But we saw that the data is not collected using random sampling. So, we should not implement Random effects model.

This leaves us with Fixed effects model with entity fixed effects as our best model for understanding impact of shall law on murder rate.

Conclusion

Based on our findings, we conclude that:

- After controlling for fixed entity effects, the model shows that having shall law leads to decrease of murder rate by 3% compared to not having shall law keeping all the other significant variables constant at significance level of 0.15
- After controlling for fixed entity effects, having shall law leads to increase of rob rate by 4% compared to not having shall law keeping all the other significant variables constant at significance level of 0.1
- After controlling for both time and entity fixed effects, the model shows that having shall law decreases the violence rate by 2% when compared to not having shall law keeping all the other significant variables constant at significance level of 0.1

  Based on findings from previous studies mentioned in the first section & our results, we believe that murder rate has decreased after the introduction of shall law but at the same time, we notice an increase in robberies as based on hypothesis of other economists specifically, John Lott & David Mustard, that this law has also been associated with an increase in property crimes involving theft of handguns.
  We also notice that the rate of violence has also decreased after the introduction of shall law which is consistent with the research of John Lott & David Mustard. We think that this could be because when guns are involved, the amount of risk involved in committing the crime increases.

As the possibility of a person carrying a gun increased because of shall law, criminals could have changed their approach towards committing crimes where there is lesser uncertainty like robberies, burglaries etc.

Also, this makes it more convenient to commit a robbery as the amount of risk involved is lesser

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