Do more Guns Reduce Crime in US??

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INTRODUCTION

Do more Guns reduce Crime?

The impact of guns on crime in America has triggered a lot of public debate. Many strongly believe that state laws enabling citizens to carry concealed handguns had reduced crime. According to this view, gun control laws take away guns from law-abiding citizens, while would-be criminals ignore those leaving potential victims defenseless. Following this view, The National Rifle Association (NRA) and many politicians across the country advance the cause of greater freedom to carry guns.

As a result, many states in the United States have passed **right-to-carry laws** (also known as a **shall-issue laws**). A Shall-issue law is one that requires that governments issue concealed carry handgun permits to any applicant who meets the necessary criteria. These criteria are the applicant must be an adult, have no significant criminal record, and no history of mental illness and successfully complete a course in firearms safety training (if required by law). If these criteria are met, the granting authority has no discretion in the awarding of the licenses, and there is no requirement of the applicant to demonstrate "good cause".

We have analyzed the historical data on crime in the U.S to answer the question "Do shall-issues law reduce crime-or not.

GUNS DATASET

Guns.csv

Sample Dataset – Imported in R

year	vio Violent Crime Rate per 100,000 population (BJS)	mur Murder Crime Rate per 100,000 population (BJS)	rob Robbery Crime Rate per 100,000 population (BJS)	incarc_rate 72-99 ONLY - Lagged Rate per 100,000 resident pop of sentenced...	pb1064	pw1064	pm1029	pop	avginc	density	stateid	all
77	1426.5	27.8	964.5	334	25.8058929	21.91194	18.15841	0.677229	15.950089	1.110212e+...	11	
77	831.8	10.7	472.6	98	5.2718396	62.96160	17.10692	17.812607	13.403532	3.724071e-01	36	
77	743.0	15.8	323.1	156	3.6813724	70.31890	18.48337	0.678334	14.056200	6.172901e-03	32	
77	706.0	11.5	287.0	85	5.0116630	65.51936	18.78835	22.352402	14.089081	1.429538e-01	6	
77	693.8	8.0	292.1	192	8.3151016	59.80103	18.56987	4.169594	13.466004	4.215544e-01	24	
77	686.8	10.2	187.9	211	5.0867400	60.00757	16.37442	8.856183	11.524441	1.637305e-01	12	
77	636.2	11.9	105.9	230	10.5465050	52.76060	19.69209	2.991683	9.344497	9.898041e-02	45	
77	630.6	9.9	280.3	87	5.3145447	62.96043	18.08612	11.386319	13.784941	2.042462e-01	17	

```
# A tibble: 23 x 2
   `as.character(guns$year)` state
   <chr>                     <int>
 1 77                           51
 2 78                           51
 3 79                           51
 4 80                           51
 5 81                           51
 6 82                           51
 7 83                           51
 8 84                           51
 9 85                           51
10 86                           51
# … with 13 more rows
```

Guns is a balanced panel of data on 50 US states, plus the District of Columbia (for a total of 51 "states"), by year for 1977 – 1999. Each observation is a given state in a given year. There is a total of 51 states × 23 years = 1173 observations.

VARIABLE DEFINITIONS

Variable	Definition
Vio	violent crime rate (incidents per 100,000 members of the population)
Rob	robbery rate (incidents per 100,000)
Mur	murder rate (incidents per 100,000)
Shall	= 1 if the state has a shall-carry law in effect in that year = 0 otherwise
incarc_rate	incarceration rate in the state in the previous year (sentenced prisoners per 100,000 residents; value for the previous year)
Density	population per square mile of land area, divided by 1000
Avginc	real per capita personal income in the state, in thousands of dollars
Pop	state population, in millions of people
pm1029	percent of state population that is male, ages 10 to 29
pw1064	percent of state population that is white, ages 10 to 64
pb1064	percent of state population that is black, ages 10 to 64
Stated	ID number of states (Alabama = 1, Alaska = 2, etc.)
Year	Year (1977-1999)

Dependent variables: VIO; ROB; MUR
Regressors: INCARC_RATE, DENSITY, AVGINC, POP
Indicator Variables: SHALL, PM1029, PW1064, PB1064
Entity: STATEID
Time Period: YEAR

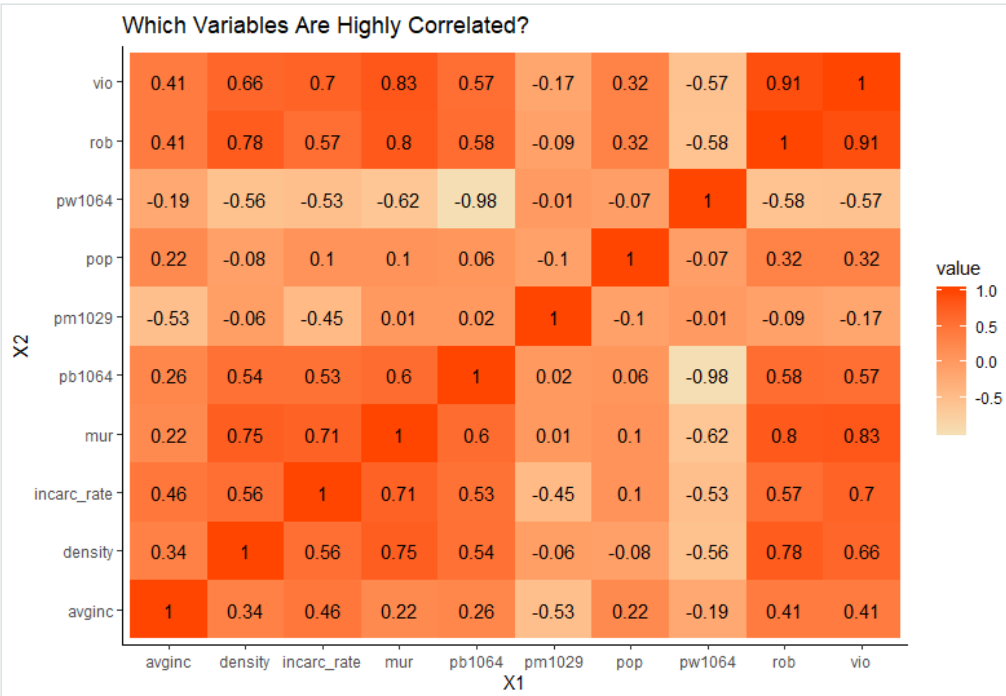
Effect of Variables on Violent Crime Rate (Expected impact according to Economic Theory)

- **SHALL**: Introduction of Shall-carry law should reduce the crime rate and therefore will have an inverse relation with the crime rate.
- **INCARC_RATE**: Increase in Incarceration rate should reduce the crime rate and therefore will have an inverse relation with the crime rate.
- **DENSITY**: The role of population density in the generation or suppression of crime has
  been the subject of debate for decades. So, we can say that it can either increase or decrease the crime rate.
- **AVGINC**: The real per capita personal income in the state should reduce the crime rate, therefore an inverse relation.
- **POP**: More the state population, more the chances violent crime rate. So, POP will have a positive relation with VIO.

- **PM1029**: Having more male population between ages 10 and 29 increase the chances of crime. Therefore, it will have positive relation with crime rate.
- **PW1064 and PB1064**: The effect of these two variables, according to economic theory, are highly contrasting. The difference because of different racial groups effect the crime rate differently and are debatable. The effect of population of blacks increase the crime rate as compared to population of whites. Competitive society in which there is an inequality in the distribution of goods, those groups with limited or restricted access to goods will be more likely to turn to crime.

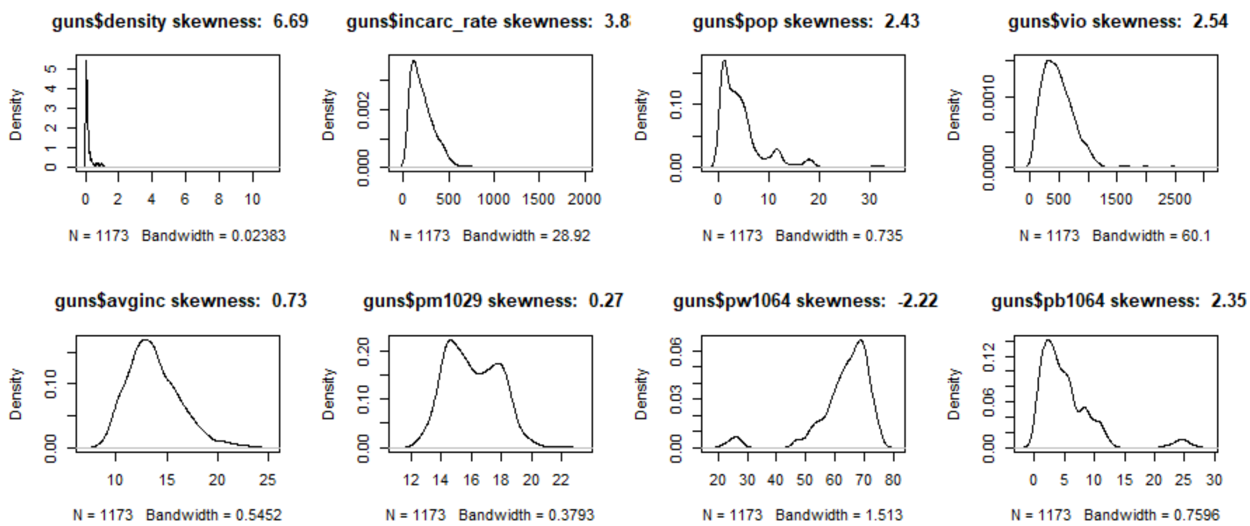
PART 1: EXPLORATORY DATA ANALYSIS -OVERVIEW

Correlation between variables – Heat map



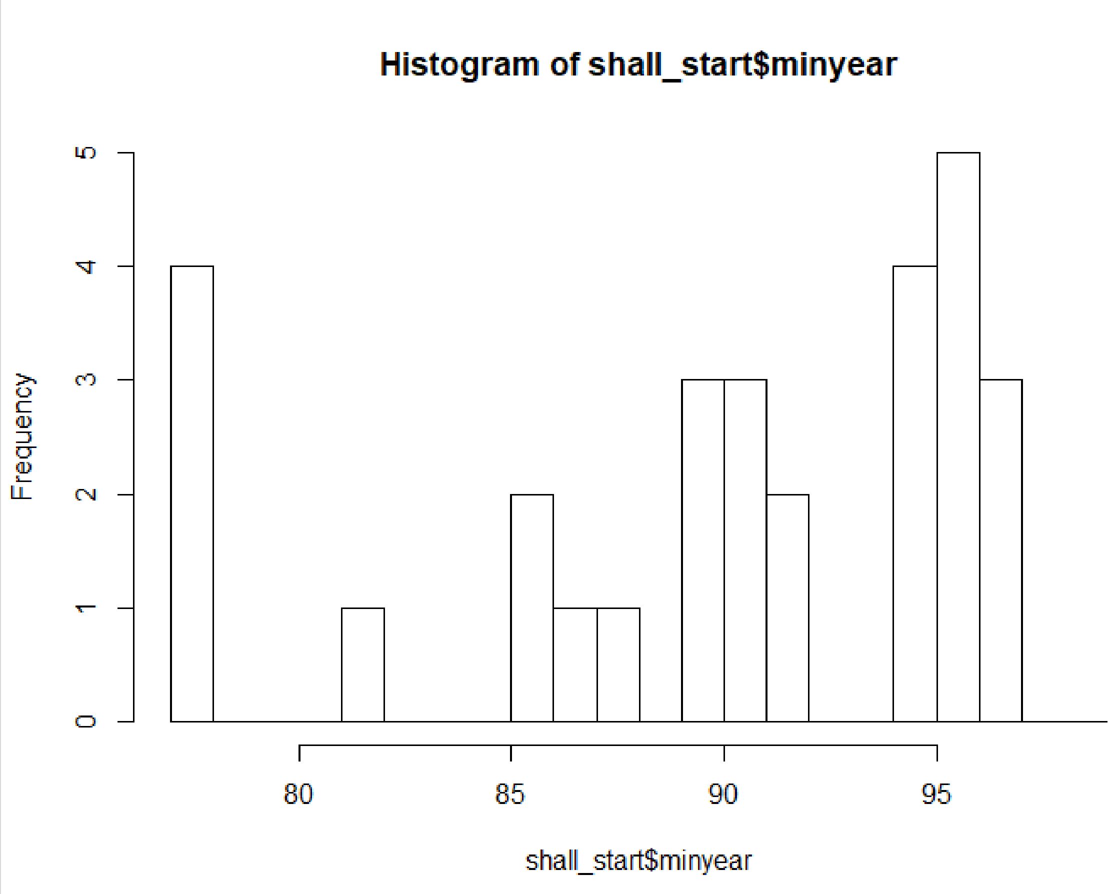
- We can see the variables PW1064 and PB1064 are highly negatively correlated (-0.98).
- Including independent variables that are highly correlated can lead to inflated Standard Errors.

NORMALITY OF VARIABLES



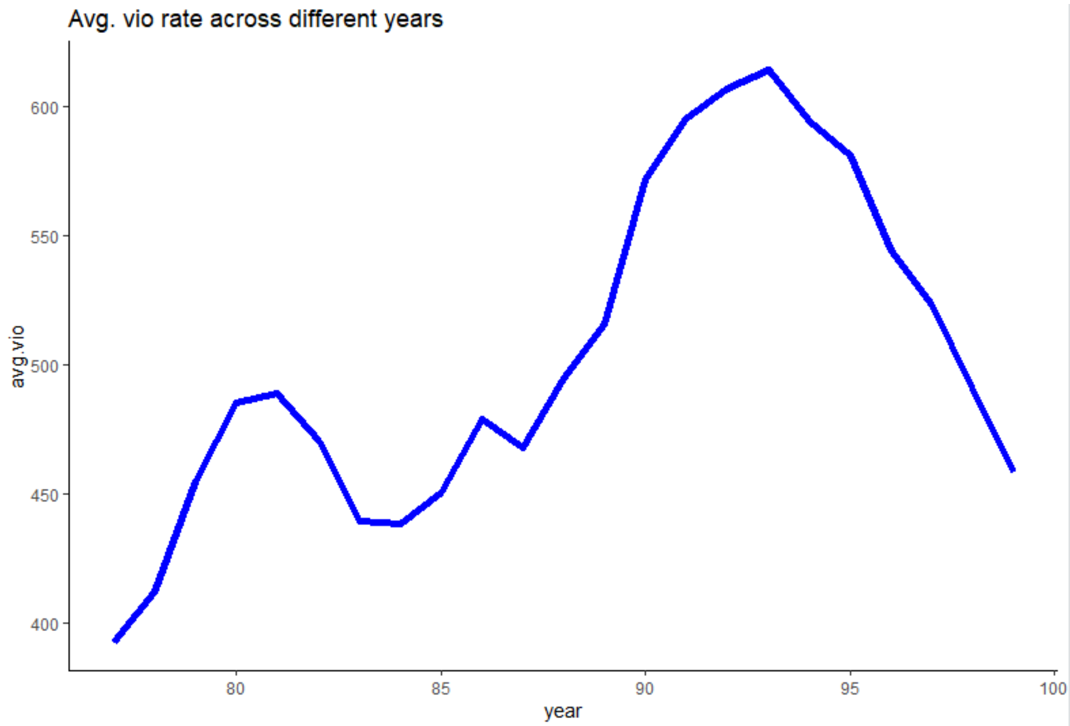
- Violence rate, Incarceration rate and density of population have high skewness (above 2.5)
- We, therefore, need to transform these three variables using logarithmic function.

GRAPH 1: Frequency of States in the years the Shall-law was introduced.



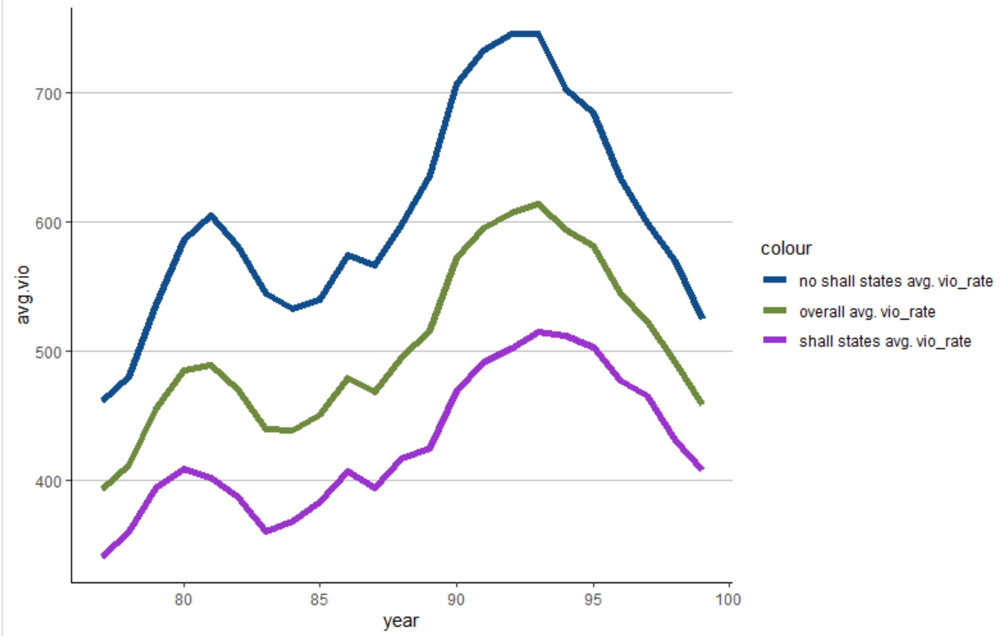
- We can say, from the graph, that 4 states have implemented Shall-issue law from the starting of the observed time period- 1977.
- 29 out of 51 states implemented the Shall-issue law in the observed time period of 23 years.

GRAPH 2: Pattern of average violent rate across different years



- From the graph, we can see that the average violent rate has been fluctuating with significant highs and lows.
- From the graph 1, we can see that more states have introduced the Shall law and therefore, we can see that there is a high incline and decline in the latter part of the time period observed from the above graph.

GRAPH 3: Average. Vio rate for overall and shall/no-shall states.



- From the above graph, we can see that the states which have implemented Shall law have low average Violence rate than the states which have not implemented Shall law in the observed time period.

Graph 4: Difference between the average Violent rate BEFORE and AFTER implementation of Shall-issue laws in United States.

- From the graph, we can see that Introduction of Shall-law has reduced crime rate over the years as compared to the crime rate when it was not introduced in the states.

Part 2: Regression for Panel Data

Pooled Ordinary Least Squares

Here we will have the following variables

- **Dependent variable:** log (violence rate)
- **Independent variables:**
    - **i.** log(incarc_rate)
    - **ii.** pb1064
    - **iii.** pm1029
    - **iv.** pop
    - **v.** avginc
    - **vi.** log(density)
    - vii. shall (categorical variable), where
      shall=1 (states which have implemented shall law)
      shall=0 (states which haven't implemented shall law)
    - **viii.** pw1064

```
> pooled_vio<-plm(log(vio)~shall+log(incarc_rate)+pb1064+pm1029+pw1064+pop+avginc+log(density),data=guns2, model="pooling")
> summary(pooled_vio) # pooled ols without white std error
Pooling Model

Call:
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pm1029 + pw1064 + pop + avginc + log(density), data = guns2,
    model = "pooling")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.241301 -0.236873  0.011587  0.257641  1.104852

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)       0.1816538  0.4902108  0.3706 0.7110307
shall1           -0.2826839  0.0283135 -9.9841 < 2.2e-16 ***
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 ***
pw1064            0.0033576  0.0070293  0.4777 0.6329816
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 ***
---
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
```

Model 1.a- pooled OLS with all the explanatory variables

```
> coeftest(pooled_vio,vcov.=vcovHC) # pooled ols with white std error

t test of coefficients:

                  Estimate Std. Error t value  Pr(>|t|)
(Intercept)      0.1816538  2.0349774  0.0893  0.928886
shall1          -0.2826839  0.0875969 -3.2271  0.001285 **
log(incarc_rate)  0.6935672  0.0905465  7.6598 3.903e-14 ***
pb1064           0.0033125  0.0545442  0.0607  0.951584
pm1029           0.1167641  0.0277694  4.2048 2.814e-05 ***
pw1064           0.0033576  0.0272660  0.1231  0.902015
pop              0.0240749  0.0073170  3.2903  0.001031 **
avginc           0.0232989  0.0183125  1.2723  0.203522
log(density)     0.0928883  0.0341217  2.7223  0.006580 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model 1.b- pooled OLS with all the explanatory variables and white's SE hence suspicion of Heteroskedasticity

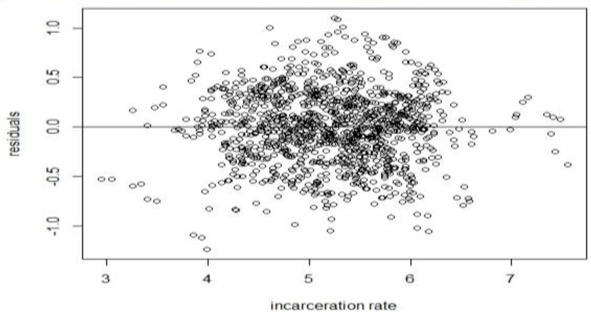
- Testing the joined significance of the pb1064 and pw1064

```
> #combined significance test
> Hnull <- c("pb1064=0","pw1064=0")
> linearHypothesis(pooled_vio,Hnull)
Linear hypothesis test

Hypothesis:
pb1064 = 0
pw1064 = 0

Model 1: restricted model
Model 2: log(vio) ~ shall + log(incarc_rate) + pb1064 + pm1029 + pw1064 +
    pop + avginc + log(density)

  Res.Df Df  Chisq Pr(>Chisq)
1   1166
2   1164  2 1.3722     0.5035
> |
```

Hypothesis test 1

- **To Check for Heteroskedasticity**
  Graph 4 – log(incarc_rate) vs residual of model 1.a which confirms Heteroskedasticity

```
#plots for heteroscedasticity
res <- residuals(pooled_vio)
yhat <- fitted(pooled_vio)
plot(log(guns2$incarc_rate),res, xlab="incarceration rate", ylab="residuals") +abline(h =0)
```



```
> #remove pw1064,pb1064
> pooled_vio2<-plm(log(vio)~shall+log(incarc_rate)+pm1029+pop+avginc+log(density),data=guns2, model="pooling")
> coeftest(pooled_vio2, vcov=vcovHC(pooled_vio2,type="HC0",cluster="group")) # pooled ols with robust std errors

t test of coefficients:

                   Estimate Std. Error t value  Pr(>|t|)
(Intercept)       0.5193308  0.7026614  0.7391 0.4600004
shall1           -0.2780539  0.0779611 -3.5666 0.0003763 ***
log(incarc_rate)  0.6781482  0.0666298 10.1779 < 2.2e-16 ***
pm1029            0.1134168  0.0227080  4.9946 6.796e-07 ***
pop               0.0245819  0.0074874  3.2831 0.0010571 **
avginc            0.0239844  0.0163878  1.4635 0.1435869
log(density)      0.0880118  0.0270546  3.2531 0.0011742 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> |
```

Model 1.c- pooled OLS with only significant explanatory variables and cluster robust SE.

Interpretation

- From the table above we can see that the states which implemented shall law have 28.3% less violent crime rate than the states which haven’t implemented the shall law keeping all the other variables constant.
- Estimates of pb1064 and pw1064 are not significantly different from zero as the p-value of both these variables are high, so we do a joined hypothesis test to verify if both these variables are insignificant. Here, our Null hypothesis will be
  H_0: pb1064 = 0 & pw1064 = 0
  H_1: At least one of them is not zero
  we’ll perform F-test for this.
  The p value for the test is 0.5035, which is high.
  So, we fail to reject the null and hence pb1064 and pw1064 are not significantly different from zero at 5% or even at 10% of level of significance.
  So, we drop these variables and run the pooled OLS again with new estimates and more accurate model.
- Also, we suspected the presence of heteroskedasticity because it is a cross-sectional data.
  As we have found out standard errors using the white test and the difference between both standard errors is significant, so this is also one of the reason to check for heteroskedasticity. To verify this, we plotted incarc_rate vs residual of the model and found that the variance for all the observations are not same, which confirms the presence of heteroskedasticity. So, our LS estimator is linear unbiased and consistent but no longer the best and the standard errors are wrong. To correct them we will use Cluster Robust Standard error

- The new model will drop two variables namely pb1064 and pw1064 ad use the Cluster Robust S.E with pooled OLS
- From this new model we can say that the states which implemented shall law have 27.8% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant.

The estimate of 28% seems a very high estimate so, we suspect a bias because of omitted variable. As we mentioned that it is a cross sectional data, there is high possibility of having unobserved Heterogeneity and if these unobserved factors are correlated with the explanatory variable than we might have an issue of endogeneity which may lead to biased and inconsistent estimator.

We might also observe Simultaneous Causality bias as if shall is implemented then, violent crime rate should go down in that state but, if violent crime rate is high in that state then shall need to be implemented and will be implemented. So, there could be some omitted factor like **effectiveness of judiciary and law** which could cause the bias. So, we will use Fixed effect with entity fixed effect model.

Fixed effect with entity fixed effect model

It controls for individual heterogeneity both observed and unobserved and is individual specific as well. Here, the coefficient estimates depend only on the variation of the dependent and explanatory variable **within entity**. It only estimates the variation in x over time for each individual that contributes to the estimated coefficient. It allows us to estimate a unbiased and consistent estimator to the variables that are endogenous to the OLS.

```
> #fixed effects
> fixed_vio<-plm(log(vio)~shall+log(incarc_rate)+pb1064+pm1029+pw1064+pop+avginc+log(density),data=guns2, model="within")
> summary(fixed_vio)
Oneway (individual) effect Within Model

Call:
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pm1029 + pw1064 + pop + avginc + log(density), data = guns2,
    model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5621921 -0.0989159  0.0089916  0.1020525  0.5887111

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall1           -0.0379065  0.0189886 -1.9963  0.046147 *
log(incarc_rate) -0.0672299  0.0282092 -2.3833  0.017327 *
pb1064            0.0952893  0.0150322  6.3390 3.352e-10 ***
pm1029           -0.0690675  0.0083143 -8.3071 2.821e-16 ***
pw1064            0.0428067  0.0052073  8.2205 5.591e-16 ***
pop               0.0243860  0.0092824  2.6271  0.008729 **
avginc           -0.0041476  0.0057273 -0.7242  0.469107
log(density)     -0.2518321  0.0859535 -2.9299  0.003460 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.562
R-Squared:      0.22362
Adj. R-Squared: 0.1832
F-statistic: 40.1082 on 8 and 1114 DF, p-value: < 2.22e-16
> coeftest(fixed_vio, vcov.=vcovHC(fixed_vio)) # robust errors

t test of coefficients:

                   Estimate Std. Error t value Pr(>|t|)
shall1           -0.0379065  0.0424329 -0.8933 0.371874
log(incarc_rate) -0.0672299  0.0681151 -0.9870 0.323855
pb1064            0.0952893  0.0311567  3.0584 0.002278 **
pm1029           -0.0690675  0.0254561 -2.7132 0.006766 **
pw1064            0.0428067  0.0143783  2.9772 0.002972 **
pop               0.0243860  0.0117827  2.0697 0.038715 *
avginc           -0.0041476  0.0129556 -0.3201 0.748923
log(density)     -0.2518321  0.1654395 -1.5222 0.128243
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Model 2.a- Fixed entity effects with all the explanatory variables

- To test for significance of avginc

```
> # Hyposthesis 2
> Hnull <- c("avginc=0")
> linearHypothesis(fixed_vio,Hnull)
Linear hypothesis test

Hypothesis:
avginc = 0

Model 1: restricted model
Model 2: log(vio) ~ shall + log(incarc_rate) + pb1064 + pm1029 + pw1064 +
    pop + avginc + log(density)

  Res.Df Df  Chisq Pr(>Chisq)
1   1115
2   1114  1 0.5244      0.469
>
```

Hypothesis test 2

```
> fixed_vio2<-plm(log(vio)~shall+log(incarc_rate)+pb1064+pm1029+pw1064+pop+log(density),data=guns2, model="within")
> summary(fixed_vio2)
Oneway (individual) effect Within Model

Call:
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pm1029 + pw1064 + pop + log(density), data = guns2, model = "within")

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

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

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall1           -0.0380101  0.0189840 -2.0022  0.045503 *
log(incarc_rate) -0.0726069  0.0272087 -2.6685  0.007729 **
pb1064            0.0940313  0.0149283  6.2989 4.307e-10 ***
pm1029           -0.0672520  0.0079256 -8.4854 < 2.2e-16 ***
pw1064            0.0425889  0.0051975  8.1941 6.872e-16 ***
pop               0.0241646  0.0092753  2.6052  0.009303 **
log(density)     -0.2503523  0.0859108 -2.9141  0.003638 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.576
R-Squared:      0.22326
Adj. R-Squared: 0.18355
F-statistic: 45.7826 on 7 and 1115 DF, p-value: < 2.22e-16
> coeftest(fixed_vio2, vcov.=vcovHC(fixed_vio2)) # robust errors

t test of coefficients:

                  Estimate Std. Error t value Pr(>|t|)
shall1           -0.038010   0.042405 -0.8963 0.370260
log(incarc_rate) -0.072607   0.065597 -1.1069 0.268591
pb1064            0.094031   0.030277  3.1057 0.001946 **
pm1029           -0.067252   0.024131 -2.7869 0.005412 **
pw1064            0.042589   0.014409  2.9558 0.003184 **
pop               0.024165   0.011504  2.1006 0.035900 *
log(density)     -0.250352   0.164700 -1.5201 0.128782
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model 2.b- Entity Fixed effects model with only significant explanatory variables and robust SE.

Interpretation

- From the regression output above in 2.a we can see that the states which implemented shall law have 3.79% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant.
- Estimates of avginc is not significantly different from zero as its p-value is high, so we do a hypothesis test to verify if both these variables are insignificant. Here, our Null hypothesis will be
  H_0: avginc = 0,
  H_1: avginc $\neq$ 0,
  we'll perform Chi square-test for this.
  The p value for the test is 0.469, which is high.
  So, we fail to reject the null and hence avginc is not significantly different from zero at 5% or even at 10% of level of significance.
  So, we drop that variable and run the FE again with new estimates and more accurate model.
- The new model will drop the variable avginc and use the Cluster Robust S.E with FE.
- From this new model we can say that the states which implemented shall law have 3.8% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant and all the estimates are significant at a high of p-value which is approximately zero.

This estimated value is quite different form Pooled OLS.

Fixed Effects model with Entity-fixed and Time-Fixed effects

In FE with fixed entities, we are not interpretation the models which are time invariant, but they can affect the model in a significant way. Some variables which might be omitted can vary over time but constant across all the states. We can solve this issue by creating a model which has both Time and Entity fixed effects. We will do so by creating a dummy variable for time and remove all the biases.

```
> fixed_vio3 <- plm(log(vio)~shall+log(incarc_rate)+pb1064+pm1029+pw1064+pop+avginc+log(density)+factor(year)-1, data=guns2, model="within")
> summary(fixed_vio3)
Oneway (individual) effect Within Model

Call:
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pm1029 + pw1064 + pop + avginc + log(density) + factor(year) -
    1, data = guns2, model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4460658 -0.0776349  0.0049193  0.0787723  0.6797810

Coefficients: (1 dropped because of singularities)
                   Estimate Std. Error t-value  Pr(>|t|)
shall0            0.0280294  0.0172992  1.6203 0.1054622
log(incarc_rate) -0.1042006  0.0281708 -3.6989 0.0002273 ***
pb1064           -0.0116159  0.0196878 -0.5900 0.5553079
pm1029            0.0790354  0.0154122  5.1281 3.461e-07 ***
pw1064           -0.0012751  0.0076177 -0.1674 0.8670976
pop               0.0060215  0.0083075  0.7248 0.4687083
avginc            0.0018515  0.0062919  0.2943 0.7686099
log(density)     -0.2539256  0.0768528 -3.3041 0.0009839 ***
factor(year)78    0.0676702  0.0280068  2.4162 0.0158464 *
factor(year)79    0.1865317  0.0286830  6.5032 1.194e-10 ***
factor(year)80    0.2485785  0.0292264  8.5053 < 2.2e-16 ***
factor(year)81    0.2569276  0.0304912  8.4263 < 2.2e-16 ***
factor(year)82    0.2505044  0.0327855  7.6407 4.710e-14 ***
factor(year)83    0.2292094  0.0358749  6.3891 2.465e-10 ***
factor(year)84    0.2715517  0.0397885  6.8249 1.456e-11 ***
factor(year)85    0.3302088  0.0435107  7.5891 6.881e-14 ***
factor(year)86    0.4184033  0.0478227  8.7490 < 2.2e-16 ***
factor(year)87    0.4274345  0.0521690  8.1933 7.056e-16 ***
factor(year)88    0.4992313  0.0569334  8.7687 < 2.2e-16 ***
factor(year)89    0.5644762  0.0613829  9.1960 < 2.2e-16 ***
factor(year)90    0.7010563  0.0743982  9.4230 < 2.2e-16 ***
factor(year)91    0.7656107  0.0780946  9.8036 < 2.2e-16 ***
factor(year)92    0.8085043  0.0824750  9.8030 < 2.2e-16 ***
factor(year)93    0.8406784  0.0856934  9.8103 < 2.2e-16 ***
factor(year)94    0.8368898  0.0895086  9.3498 < 2.2e-16 ***
factor(year)95    0.8428252  0.0933387  9.0298 < 2.2e-16 ***
factor(year)96    0.7985925  0.0970704  8.2269 5.418e-16 ***
factor(year)97    0.7878690  0.1006015  7.8316 1.135e-14 ***
factor(year)98    0.7426847  0.1046289  7.0983 2.270e-12 ***
factor(year)99    0.6931981  0.1081344  6.4105 2.154e-10 ***
---
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:      0.42559
Adj. R-Squared: 0.38351
F-statistic: 26.9695 on 30 and 1092 DF, p-value: < 2.22e-16
> |
```

Model 3.a- Fixed entity and Fixed Time effects with all the explanatory variables

```
> coeftest(fixed_vio3, vcov.=vcovHC(fixed_vio3))

t test of coefficients:

                   Estimate Std. Error t value  Pr(>|t|)
shall0            0.0280294  0.0385010  0.7280 0.4667579
log(incarc_rate) -0.1042006  0.0685286 -1.5205 0.1286645
pb1064           -0.0116159  0.0507158 -0.2290 0.8188808
pm1029            0.0790354  0.0530691  1.4893 0.1366992
pw1064           -0.0012751  0.0258423 -0.0493 0.9606563
pop               0.0060215  0.0129627  0.4645 0.6423612
avginc            0.0018515  0.0157468  0.1176 0.9064228
log(density)     -0.2539256  0.1890355 -1.3433 0.1794639
factor(year)78    0.0676702  0.0158566  4.2676 2.147e-05 ***
factor(year)79    0.1865317  0.0272989  6.8329 1.380e-11 ***
factor(year)80    0.2485785  0.0389244  6.3862 2.511e-10 ***
factor(year)81    0.2569276  0.0431608  5.9528 3.548e-09 ***
factor(year)82    0.2505044  0.0539880  4.6400 3.906e-06 ***
factor(year)83    0.2292094  0.0668072  3.4309 0.0006241 ***
factor(year)84    0.2715517  0.0817785  3.3206 0.0009280 ***
factor(year)85    0.3302088  0.0968687  3.4088 0.0006762 ***
factor(year)86    0.4184033  0.1130290  3.7017 0.0002248 ***
factor(year)87    0.4274345  0.1297172  3.2951 0.0010154 **
factor(year)88    0.4992313  0.1443966  3.4574 0.0005665 ***
factor(year)89    0.5644762  0.1588095  3.5544 0.0003950 ***
factor(year)90    0.7010563  0.2059380  3.4042 0.0006877 ***
factor(year)91    0.7656107  0.2156107  3.5509 0.0004003 ***
factor(year)92    0.8085043  0.2281836  3.5432 0.0004120 ***
factor(year)93    0.8406784  0.2381641  3.5298 0.0004331 ***
factor(year)94    0.8368898  0.2468629  3.3901 0.0007237 ***
factor(year)95    0.8428252  0.2584489  3.2611 0.0011442 **
factor(year)96    0.7985925  0.2702574  2.9549 0.0031945 **
factor(year)97    0.7878690  0.2779692  2.8344 0.0046761 **
factor(year)98    0.7426847  0.2899334  2.5616 0.0105534 *
factor(year)99    0.6931981  0.3001744  2.3093 0.0211119 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>
```

Model 3.b- Fixed entity and Fixed Time effects with all the explanatory variables with robust SE

```
> # Hyposthesis 3
> Hnull <- c("pb1064=0","pop=0","avginc=0","pw1064=0")
> linearHypothesis(fixed_vio3,Hnull)
Linear hypothesis test

Hypothesis:
pb1064 = 0
pop = 0
avginc = 0
pw1064 = 0

Model 1: restricted model
Model 2: log(vio) ~ shall + log(incarc_rate) + pb1064 + pm1029 + pw1064 +
    pop + avginc + log(density) + factor(year) - 1

  Res.Df Df  Chisq Pr(>Chisq)
1   1096
2   1092  4 1.2762     0.8654
>
```

Hypothesis 3

```
> fixed_vio4 <- plm(log(vio)~log(incarc_rate)+pm1029+log(density)+shall+factor(year)-1, data=guns2, model="within")
> summary(fixed_vio4)
Oneway (individual) effect Within Model

Call:
plm(formula = log(vio) ~ log(incarc_rate) + pm1029 + log(density) +
    shall + factor(year) - 1, data = guns2, model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4429406 -0.0774122  0.0051626  0.0785641  0.6796979

Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.100500   0.027696 -3.6287 0.0002980 ***
pm1029            0.076889   0.010840  7.0930 2.350e-12 ***
log(density)     -0.238238   0.066390 -3.5885 0.0003473 ***
shall0            0.028818   0.016815  1.7138 0.0868507 .
factor(year)78    0.067671   0.027600  2.4519 0.0143670 *
factor(year)79    0.185452   0.027945  6.6362 5.049e-11 ***
factor(year)80    0.245724   0.028304  8.6816 < 2.2e-16 ***
factor(year)81    0.253555   0.028856  8.7869 < 2.2e-16 ***
factor(year)82    0.245901   0.030358  8.1000 1.454e-15 ***
factor(year)83    0.224037   0.032424  6.9096 8.229e-12 ***
factor(year)84    0.266666   0.034426  7.7462 2.148e-14 ***
factor(year)85    0.325099   0.036616  8.8785 < 2.2e-16 ***
factor(year)86    0.413072   0.039360 10.4947 < 2.2e-16 ***
factor(year)87    0.421620   0.042133 10.0069 < 2.2e-16 ***
factor(year)88    0.492966   0.044943 10.9687 < 2.2e-16 ***
factor(year)89    0.557756   0.047630 11.7103 < 2.2e-16 ***
factor(year)90    0.690794   0.050965 13.5543 < 2.2e-16 ***
factor(year)91    0.754124   0.053891 13.9934 < 2.2e-16 ***
factor(year)92    0.796624   0.056339 14.1399 < 2.2e-16 ***
factor(year)93    0.828054   0.058362 14.1883 < 2.2e-16 ***
factor(year)94    0.823881   0.060380 13.6449 < 2.2e-16 ***
factor(year)95    0.829268   0.062673 13.2316 < 2.2e-16 ***
factor(year)96    0.784634   0.064729 12.1219 < 2.2e-16 ***
factor(year)97    0.773790   0.066283 11.6740 < 2.2e-16 ***
factor(year)98    0.728803   0.067552 10.7888 < 2.2e-16 ***
factor(year)99    0.678991   0.068681  9.8862 < 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: 21.157
R-Squared:      0.42492
Adj. R-Squared: 0.38504
F-statistic: 31.1469 on 26 and 1096 DF, p-value: < 2.22e-16
>
```

Model 3.c- Fixed entity and Fixed Time effects with only significant explanatory variables.

```
> coeftest(fixed_vio4, vcov.=vcovHC(fixed_vio4))

t test of coefficients:

                   Estimate Std. Error t value  Pr(>|t|)
log(incarc_rate) -0.1005002  0.0694234 -1.4476 0.1480034
pm1029            0.0768889  0.0297885  2.5812 0.0099760 **
log(density)     -0.2382382  0.1541333 -1.5457 0.1224747
shall0            0.0288178  0.0415246  0.6940 0.4878335
factor(year)78    0.0676705  0.0099967  6.7693 2.105e-11 ***
factor(year)79    0.1854520  0.0200617  9.2441 < 2.2e-16 ***
factor(year)80    0.2457236  0.0299570  8.2025 6.539e-16 ***
factor(year)81    0.2535553  0.0316267  8.0171 2.758e-15 ***
factor(year)82    0.2459009  0.0400667  6.1373 1.171e-09 ***
factor(year)83    0.2240371  0.0485739  4.6123 4.451e-06 ***
factor(year)84    0.2666658  0.0580432  4.5943 4.846e-06 ***
factor(year)85    0.3250987  0.0683193  4.7585 2.211e-06 ***
factor(year)86    0.4130719  0.0825010  5.0069 6.442e-07 ***
factor(year)87    0.4216200  0.0953519  4.4217 1.077e-05 ***
factor(year)88    0.4929663  0.1035354  4.7613 2.181e-06 ***
factor(year)89    0.5577559  0.1146121  4.8665 1.302e-06 ***
factor(year)90    0.6907939  0.1265930  5.4568 5.992e-08 ***
factor(year)91    0.7541243  0.1346314  5.6014 2.688e-08 ***
factor(year)92    0.7966235  0.1426721  5.5836 2.969e-08 ***
factor(year)93    0.8280542  0.1491026  5.5536 3.511e-08 ***
factor(year)94    0.8238814  0.1545358  5.3313 1.183e-07 ***
factor(year)95    0.8292682  0.1598135  5.1890 2.518e-07 ***
factor(year)96    0.7846343  0.1670895  4.6959 2.991e-06 ***
factor(year)97    0.7737903  0.1723924  4.4885 7.929e-06 ***
factor(year)98    0.7288026  0.1770999  4.1152 4.158e-05 ***
factor(year)99    0.6789909  0.1809402  3.7526 0.0001842 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>
```

Model 3.d- Fixed entity and Fixed Time effects with only significant explanatory variables with Robust SE.

```
> # Hyposthesis 4
> #Joint signifcance of Instrument year
> Hnull <- c("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")
> linearHypothesis(fixed_vio4,Hnull)
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(vio) ~ log(incarc_rate) + pm1029 + log(density) + shall +
    factor(year) - 1

  Res.Df Df  Chisq Pr(>Chisq)
1   1118
2   1096 22 482.08  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
> #Highly Significant
> |
```

Hypothesis 4

<u>Interpretation</u>:

- From the regression output above we can see that the states which implemented shall law have 2.8% less violent crime rate than the states which haven’t implemented the shall law keeping all the other variables constant.
- Estimates of pb1064, pop, avginc and pw1064 are not significantly different from zero as its p-value is high, so we do a joined hypothesis test to verify if both these variables are insignificant. Here, our Null hypothesis will be
  H_0: pb1064, pop, avginc and pw1064 = 0,
  H_1: At least one of them is not zero
  we’ll perform F-test for this.
  The p value for the test is 0.8654 which is high.
  So, we fail to reject the null and hence pb1064, pop, avginc and pw1064 are not significantly different from zero at 5% or even at 10% of level of significance.
  So, we drop these variable and run the FE with entity fixed and time fixed effects again with new estimates and more accurate model.
- The new model will drop the variables pb1064, pop, avginc and pw1064 and use the Cluster Robust S.E with FE.

- From this new model we can say that the states which implemented shall law have 2.88% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant and all the estimates are significant at a high of p-value which is approximately zero. Here shall is also significant and its estimate is very different form pooled OLS as we have removed all the biases.
- Here we must check the joined significance of all the years, so we did f test for the same.
  H0: the estimator of all the years is zero
  H1: at least one of the estimators is not zero.
  We get a p value which is almost zero, so we reject the null and hence we conclude that the we have a time effect and all years are significant.

Random Effect model

```
> # Random effects
>
> random_vio <- plm(log(vio)~log(incarc_rate)+pb1064+pm1029+pop+avginc+log(density)+shall+pw1064, data=guns2, model="random")
> summary(random_vio)
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pm1029 +
    pop + avginc + log(density) + shall + pw1064, data = guns2,
    model = "random")

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

Effects:
                  var std.dev share
idiosyncratic 0.02564 0.16012 0.224
individual    0.08882 0.29803 0.776
theta: 0.8887

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5436004 -0.1032318  0.0067898  0.1127664  0.5318024

Coefficients:
                   Estimate Std. Error z-value  Pr(>|z|)
(Intercept)       3.7089892  0.4113808  9.0160 < 2.2e-16 ***
log(incarc_rate)  0.0011089  0.0283521  0.0391  0.968800
pb1064            0.1117660  0.0129132  8.6552 < 2.2e-16 ***
pm1029           -0.0407458  0.0080205 -5.0802  3.77e-07 ***
pop               0.0217939  0.0063425  3.4362  0.000590 ***
avginc           -0.0062443  0.0058167 -1.0735  0.283037
log(density)      0.0611245  0.0300360  2.0350  0.041847 *
shall1           -0.0688798  0.0192294 -3.5820  0.000341 ***
pw1064            0.0401063  0.0052927  7.5776  3.52e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    42.39
Residual Sum of Squares: 32.84
R-Squared:      0.22527
Adj. R-Squared: 0.21995
Chisq: 338.468 on 8 DF, p-value: < 2.22e-16
> |
```

Model 4.a – Random effects with all the explanatory variables

- Testing the significance of log(incarc_rate) and avginc

```
> # Hypothesis 5
> Hnull <- c("avginc=0","log(incarc_rate)=0")
> linearHypothesis(random_vio,Hnull)
Linear hypothesis test

Hypothesis:
avginc = 0
log(incarc_rate) = 0

Model 1: restricted model
Model 2: log(vio) ~ log(incarc_rate) + pb1064 + pm1029 + pop + avginc +
    log(density) + shall + pw1064

  Res.Df Df  Chisq Pr(>Chisq)
1   1166
2   1164  2 1.2045     0.5476
> |
```

Hypothesis 5

```
> random_vio2<-plm(log(vio)~pb1064+pm1029+pop+log(density)+shall+pw1064,data=guns2, model="random")
> summary(random_vio2)
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = log(vio) ~ pb1064 + pm1029 + pop + log(density) +
    shall + pw1064, data = guns2, model = "random")

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

Effects:
                  var std.dev share
idiosyncratic 0.02577 0.16053 0.106
individual    0.21728 0.46614 0.894
theta: 0.9284

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.542232 -0.098509  0.012292  0.107995  0.516199

Coefficients:
               Estimate Std. Error  z-value  Pr(>|z|)
(Intercept)   3.6996934  0.3920307   9.4373 < 2.2e-16 ***
pb1064        0.0993713  0.0127115   7.8174 5.392e-15 ***
pm1029       -0.0392529  0.0038419 -10.2170 < 2.2e-16 ***
pop           0.0156832  0.0072823   2.1536  0.031272 *
log(density)  0.0369337  0.0412075   0.8963  0.370099
shall1       -0.0596267  0.0187883  -3.1736  0.001506 **
pw1064        0.0391065  0.0049876   7.8407 4.479e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    39.107
Residual Sum of Squares: 30.756
R-Squared:      0.21353
Adj. R-Squared: 0.20948
Chisq: 316.571 on 6 DF, p-value: < 2.22e-16
> |
```

Model 4.b – Random effects with significant explanatory variables

```
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pm1029 + pw1064 + pop + avginc + log(density) + factor(year) -
    1, data = guns2, model = "random")

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

Effects:
                  var std.dev share
idiosyncratic 0.01935 0.13911 0.175
individual    0.09129 0.30214 0.825
theta: 0.9044

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5512289 -0.0849057  0.0082914  0.0918548  0.6710818

Coefficients:
                  Estimate Std. Error z-value  Pr(>|z|)
shall0           3.3304777  0.4728270  7.0438 1.871e-12 ***
shall1           3.2936184  0.4747906  6.9370 4.005e-12 ***
log(incarc_rate) 0.0059774  0.0279815  0.2136 0.8308433
pb1064           0.0625153  0.0170503  3.6665 0.0002459 ***
pm1029           0.0474418  0.0153458  3.0915 0.0019914 **
pw1064           0.0202447  0.0072758  2.7825 0.0053947 **
pop              0.0134875  0.0062051  2.1736 0.0297334 *
avginc           0.0127489  0.0062612  2.0362 0.0417334 *
log(density)     0.0823567  0.0303965  2.7094 0.0067402 **
factor(year)78   0.0463184  0.0295252  1.5688 0.1167001
factor(year)79   0.1465228  0.0299959  4.8848 1.036e-06 ***
factor(year)80   0.1985507  0.0303894  6.5335 6.423e-11 ***
factor(year)81   0.1913684  0.0313454  6.1051 1.027e-09 ***
factor(year)82   0.1626215  0.0332368  4.8928 9.941e-07 ***
factor(year)83   0.1173903  0.0358313  3.2762 0.0010522 **
factor(year)84   0.1366263  0.0391462  3.4902 0.0004827 ***
factor(year)85   0.1769841  0.0424645  4.1678 3.075e-05 ***
factor(year)86   0.2456587  0.0464082  5.2934 1.200e-07 ***
factor(year)87   0.2356337  0.0504052  4.6748 2.943e-06 ***
factor(year)88   0.2866185  0.0547501  5.2350 1.650e-07 ***
factor(year)89   0.3316382  0.0587879  5.6413 1.688e-08 ***
factor(year)90   0.4048932  0.0700137  5.7831 7.336e-09 ***
factor(year)91   0.4529006  0.0734696  6.1645 7.072e-10 ***
factor(year)92   0.4746393  0.0773391  6.1371 8.403e-10 ***
factor(year)93   0.4901758  0.0801620  6.1148 9.667e-10 ***
factor(year)94   0.4674820  0.0834961  5.5988 2.158e-08 ***
factor(year)95   0.4539149  0.0868862  5.2242 1.749e-07 ***
factor(year)96   0.3910963  0.0901778  4.3369 1.445e-05 ***
factor(year)97   0.3620888  0.0932037  3.8849 0.0001024 ***
factor(year)98   0.2948315  0.0965548  3.0535 0.0022618 **
factor(year)99   0.2260940  0.0994720  2.2729 0.0230297 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    40.915
Residual Sum of Squares: 24.792
```

Model 4.c – Random effects with Time effects with all explanatory variables

```
plm(formula = log(vio) ~ shall + pb1064 + pm1029 + pw1064 + pop +
    avginc + log(density) + factor(year) - 1, data = guns2, model = "random")

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

Effects:
                  var std.dev share
idiosyncratic 0.01958 0.13991  0.08
individual    0.22398 0.47326  0.92
theta: 0.9385

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5226177 -0.0797926  0.0085863  0.0892511  0.6745900

Coefficients:
                 Estimate Std. Error z-value  Pr(>|z|)
shall0          3.6247120  0.4523300  8.0134 1.116e-15 ***
shall1          3.5917360  0.4548223  7.8970 2.857e-15 ***
pb1064          0.0409583  0.0178630  2.2929 0.0218530 *
pm1029          0.0577524  0.0152388  3.7898 0.0001508 ***
pw1064          0.0147376  0.0072921  2.0210 0.0432764 *
pop             0.0057732  0.0070386  0.8202 0.4120898
avginc          0.0096855  0.0062106  1.5595 0.1188749
log(density)    0.0572540  0.0405589  1.4116 0.1580608
factor(year)78 0.0510333  0.0285095  1.7900 0.0734466 .
factor(year)79 0.1543131  0.0288669  5.3457 9.008e-08 ***
factor(year)80 0.2083774  0.0292001  7.1362 9.596e-13 ***
factor(year)81 0.2043641  0.0300601  6.7985 1.057e-11 ***
factor(year)82 0.1790572  0.0313772  5.7066 1.152e-08 ***
factor(year)83 0.1379547  0.0332849  4.1447 3.403e-05 ***
factor(year)84 0.1625694  0.0364551  4.4594 8.217e-06 ***
factor(year)85 0.2072046  0.0396174  5.2301 1.694e-07 ***
factor(year)86 0.2801229  0.0432475  6.4772 9.344e-11 ***
factor(year)87 0.2743947  0.0469793  5.8408 5.196e-09 ***
factor(year)88 0.3301708  0.0511319  6.4572 1.066e-10 ***
factor(year)89 0.3797174  0.0549349  6.9121 4.774e-12 ***
factor(year)90 0.4672159  0.0658579  7.0943 1.300e-12 ***
factor(year)91 0.5183275  0.0688666  7.5265 5.210e-14 ***
factor(year)92 0.5444808  0.0725015  7.5099 5.916e-14 ***
factor(year)93 0.5634186  0.0750998  7.5023 6.273e-14 ***
factor(year)94 0.5447128  0.0782640  6.9599 3.404e-12 ***
factor(year)95 0.5345995  0.0811535  6.5875 4.473e-11 ***
factor(year)96 0.4751758  0.0840225  5.6553 1.555e-08 ***
factor(year)97 0.4498008  0.0867897  5.1827 2.188e-07 ***
factor(year)98 0.3870962  0.0899104  4.3054 1.667e-05 ***
factor(year)99 0.3224191  0.0926512  3.4799 0.0005016 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    38.5
Residual Sum of Squares: 23.103
R-Squared:      0.39993
Adj. R-Squared: 0.3847
Chisq: 761.763 on 30 DF, p-value: < 2.22e-16
```

Model 4.d – Random effects with Time effects with only significant explanatory variables and Robust SE.

```
# Hypothesis 6
phtest(fixed_vio4,random_vio4) # hausman test
```

```
        Hausman Test

data:  log(vio) ~ log(incarc_rate) + pm1029 + log(density) + shall +  ...
chisq = 129.88, df = 25, p-value = 3.875e-16
alternative hypothesis: one model is inconsistent
```

Hypothesis 6

Interpretation:

- From the regression output above we can see that the states which implemented shall law have 6.88% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant in Random effect model with all the explanatory variables.
- Estimates of log(incarc_rate) and avginc are not significantly different from zero as its p-value is high, so we do a joined hypothesis test to verify if both these variables are insignificant. Here, our Null hypothesis will be
- H_0: log(incarc_rate) =0 and avginc = 0,
  H_1: At least one of them is not zero
  we'll perform F-test for this.
  The p value for the test is 0.5474 which is high.
- So, we fail to reject the null and hence log(incarc_rate) and avginc are not significantly different from zero at 5% or even at 10% of level of significance.
- So, we drop these variable and run the RE again with new estimates and more accurate model. The states which implemented shall law have 5.96% less violent crime rate than the states which haven't implemented the shall law keeping all the other variables constant in Random effect model with all the explanatory variables.
- Now we will estimate random effect model with time effects as well. Here we can see that the log(incarc_rate) is not significant.
- The new model will drop the variables log(incarc_rate) use the Cluster Robust S.E.
- To compare between Random effect and fixed effect model we did an Hausman test between model 3.d and model 4.d
  H0: both the parameters are converging to the true parameter
  H1: only fixed effect parameter converges to the true parameter
  We can see that the p value is 0.000000 which is way smaller than the alpha level of 0.05, hence we reject the null and say that fixed effect with both entity and time effects is a significant model.
  Also, we can see that the data has information for all the states and sample is not randomly selected from the population, so it isn't advisable to use Random effect model and, we have little concern of endogeneity.
  Overall the best model is **entity and time fixed effect model.**

PART 3 - CONCLUSION

We have conflicting results from the visualization and regression fronts. These might be due to

- **Omitted Variable Bias** -There might be important variables that vary between states and over time that are omitted from the regression model. For example, other policy measures that are related to the implementation of shall issue laws and that affect crime rates.
- **Simultaneous causality** - If there are many violent crimes this may induce policy makers to change concealed weapons laws.

We conclude that Estimate of "Fixed Effects with entity-fixed and time-fixed (3.d)" is the best model as it accounts for the above problems. But as we can see from the results, the coefficient of the shall law is not statistically significant. Hence, we can conclude by saying that the shall (weapon concealment) law has no significant effect on the violent crime rate. In other words, the shall law does not have a significant effect in reducing crimes.

Hence, the government must take more vigilant and stringent measures in order to effectively reduce the crime rate.