Effect of shall issue laws on crime rate.

BUAN 6312.001 **Applied Econometrics and Time Series Analysis**

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ABSTRACT

Gun laws are a cause for great discussions in this country. This paper focuses on the laws that enable/restrict an individual to carry guns and its simultaneous effects on the crime rates. Permitting the right to carry concealed handguns has many disparate views, with proponents of the law stating that it would be of critical help to people to enable them to defend themselves against outside threat. The critics of this law, though believe that, legalizing this would lead to increased violence for trivial incidents and the possibility of accidental shootings.

In the following study, we direct our attention towards the effects of the shall issue laws in the 51 states in America over 23 years. Various statistical models are run in an effort to study the trends in crime rates before and after the shall issue laws have been introduced. We also study the effects of factors like income, incarceration, population etc.

DATA DESCRIPTION

This 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. The attributes in the data are explained below.

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
stateid	ID number of states (Alabama = 1, Alaska = 2, etc.)
year	Year (1977-1999)

The shall variable indicates whether the shall issue law has been issued in that particular state or not. We could study the trend of crime rates is association with the shall law. The '*incarc_rate'* variable gives us the number of sentenced prisoners per 100,000 residents in the previous year. This variable is directly proportionate with the crime rate. We also have the percent of young males, the white and black population, as these variables are linked with crime rate by theory.

Murder Rate and Shall Issue over Years

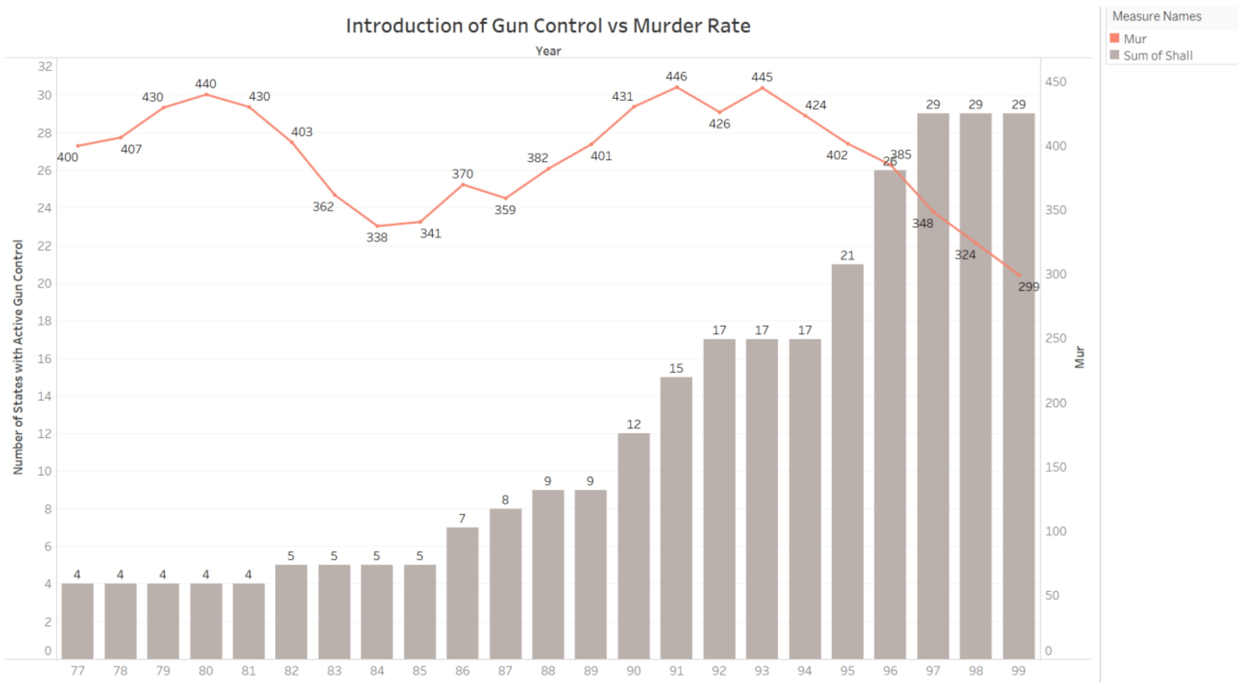

Figure 1: Introduction of Gun Control vs Violence Rate

ViolenceRate and Shall Issue over Years

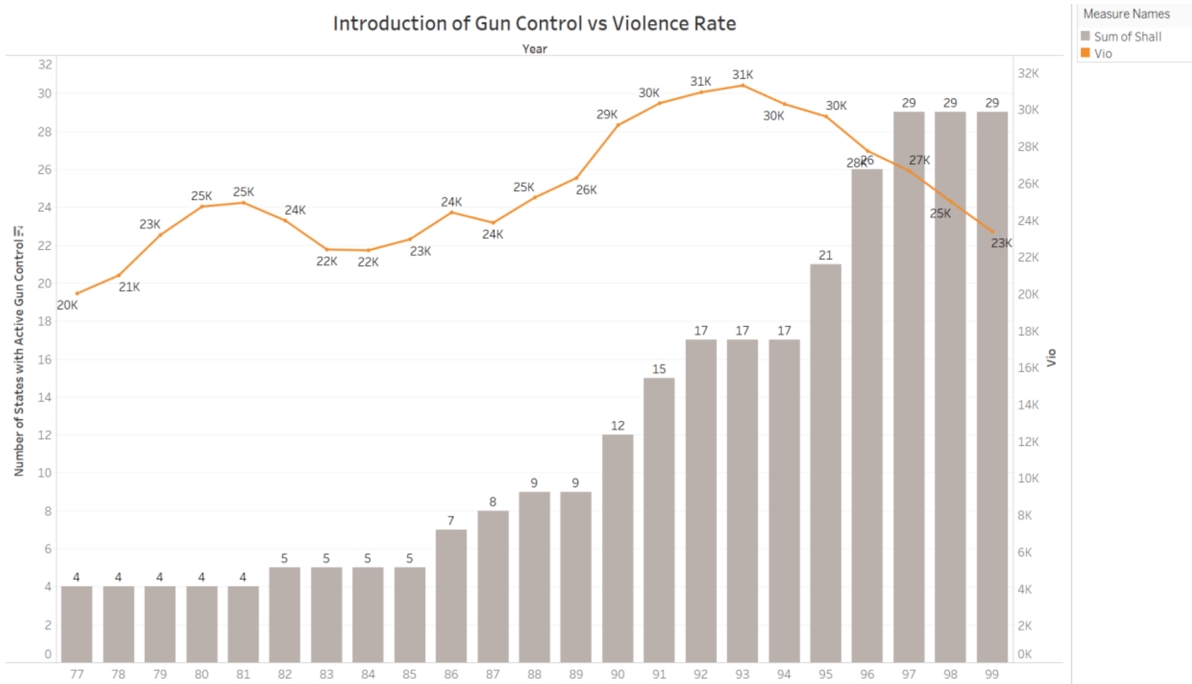

Figure 2:Introduction of Gun Control vs Violence Rate

Robbery Rate and Shall Issue Over Years

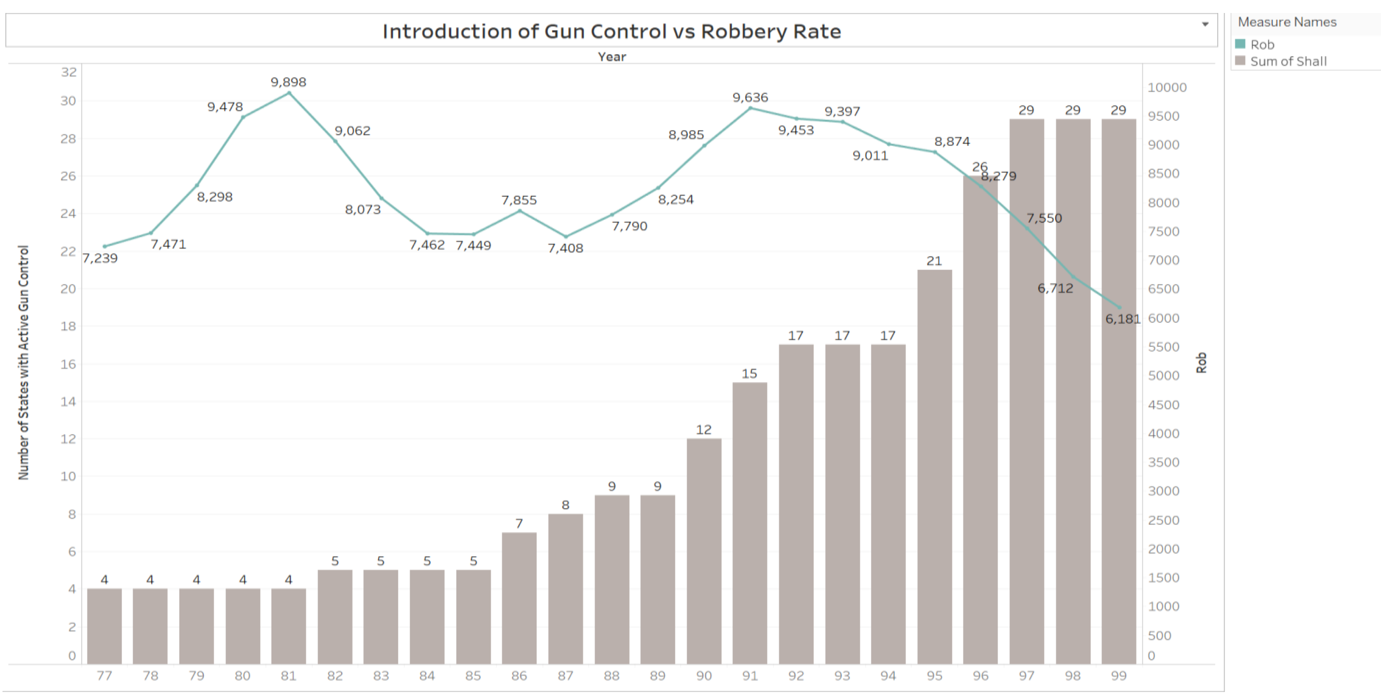

Figure 3:Introduction of Gun Control vs Robbery Rate

Correlation b/w CrimeRate and Density

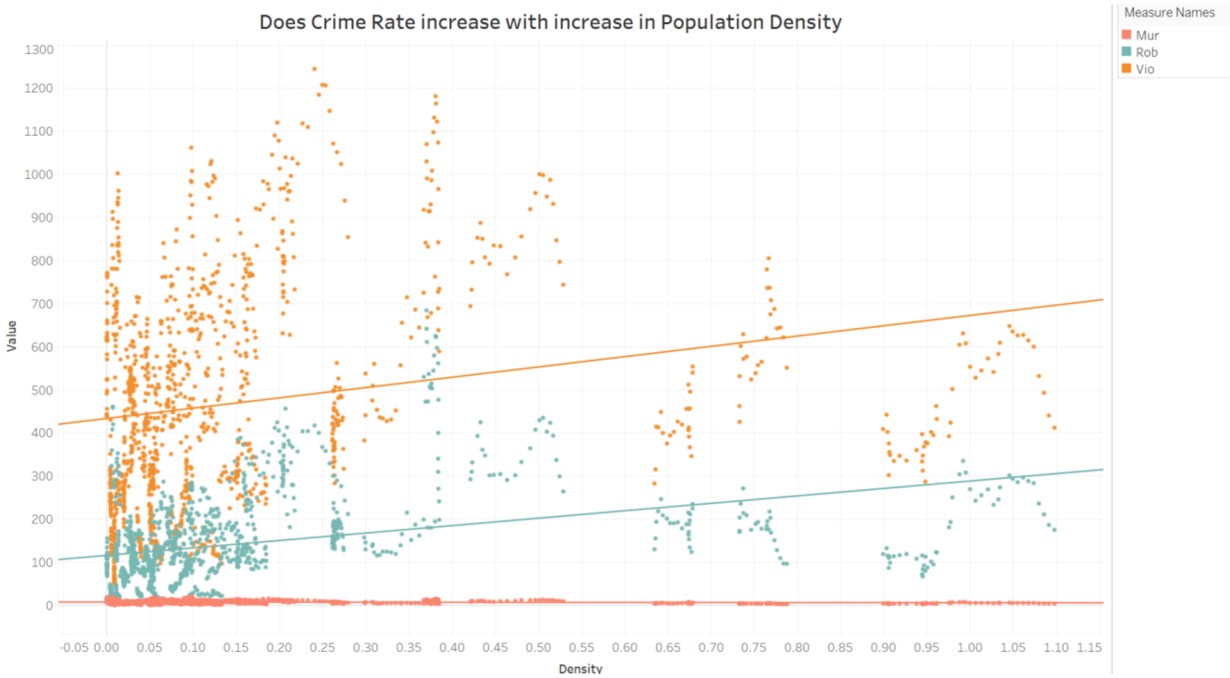

Figure 4:Does crime rate increase with Population Density?

Correlation Matrix of all variables

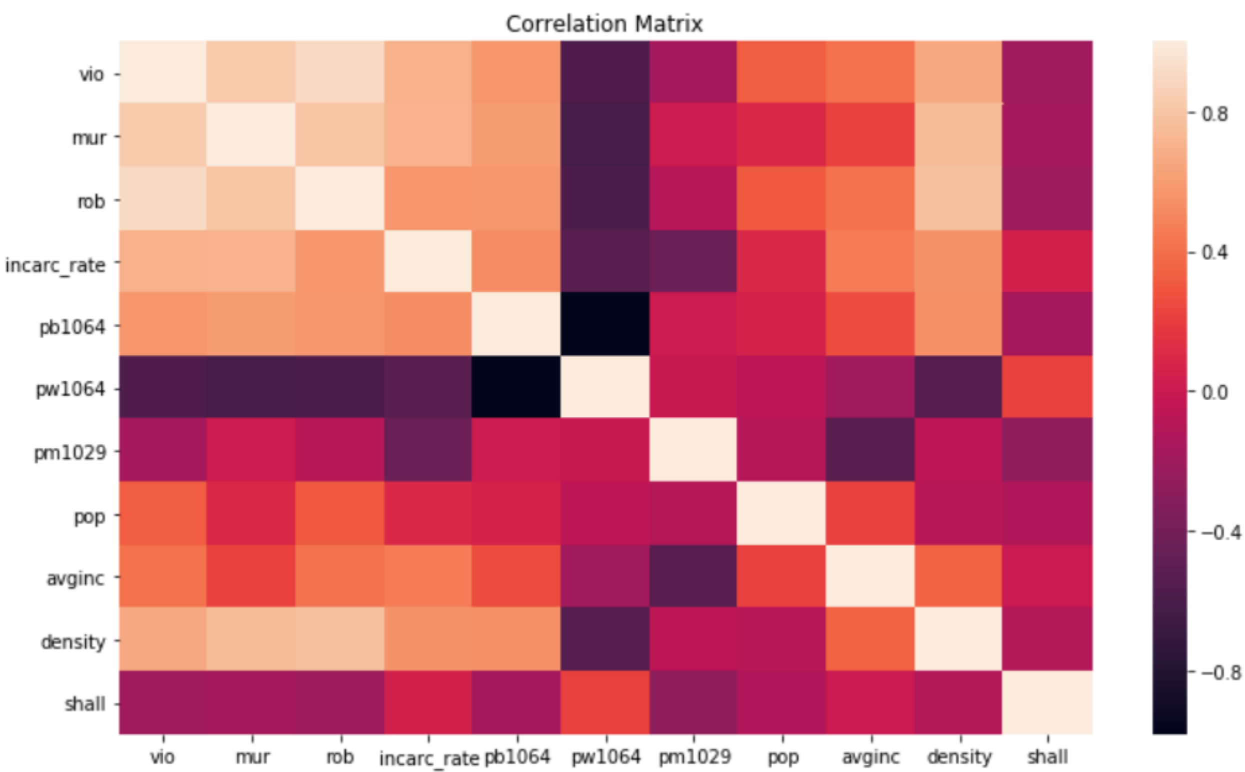

Figure 5: Correlation Matrix

State 12's Crime, Robbery and Murder Rate before and after shall carry law is passed

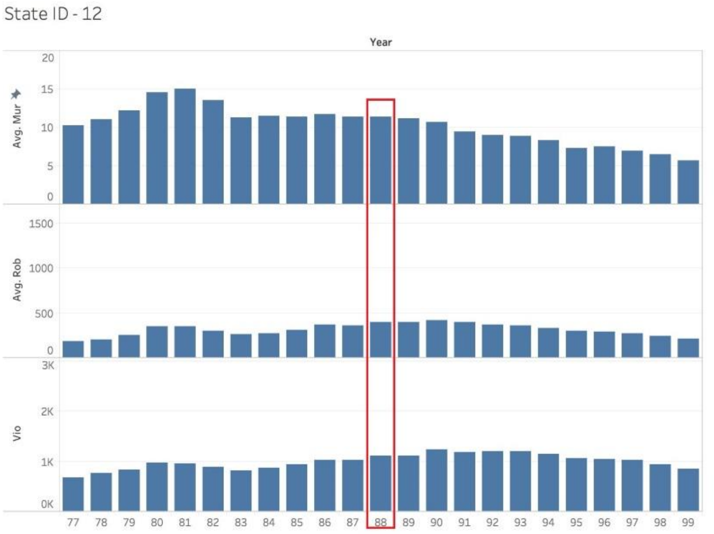

Figure 6: crime statistics for state 12 before and after shall carry law is passed

State 46's Crime, Robbery and Murder Rate before and after shall carry law is passed

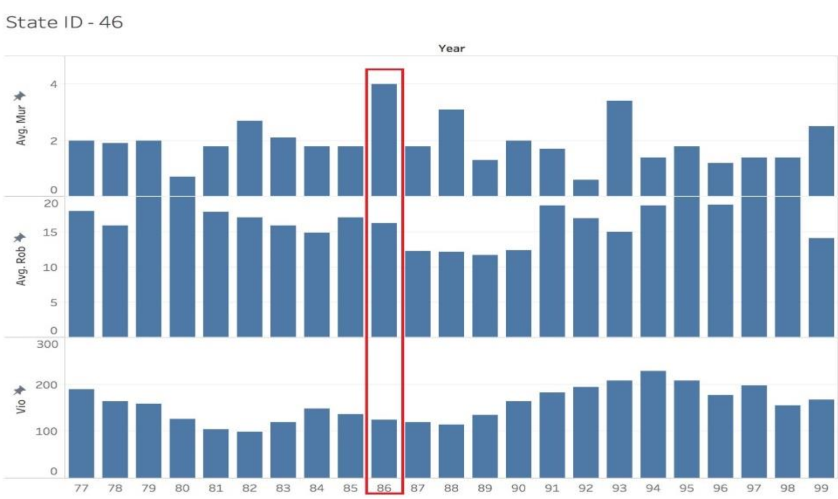

Figure 7: crime statistics for state 46 before and after shall carry law is passed

State 38's Crime, Robbery and Murder Rate before and after shall carry law is passed

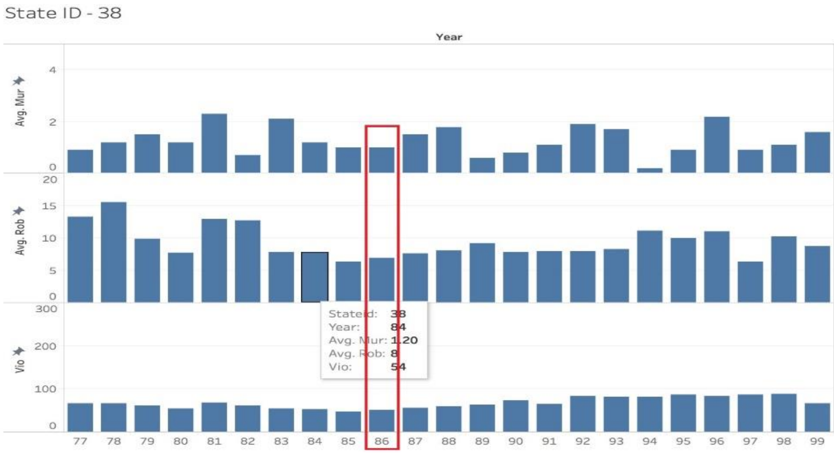

Figure 8: crime statistics for state 38 before and after shall carry law is passed

Figure 5 shows us the correlation between all the variables in the data; there is high negative correlation between percent of state population that is white, ages 10 to 64 and violent crime rate, robbery rate and murder rate. There is also high positive correlation between density and robbery rate and murder rate. Figure 4 also validates the point that as density increases, on average, the robbery rate and murder rate tend to increase as well. Figure 1-3 shows us the trend of violent crime rate, robbery rate and murder rate as well as number of states which have shall carry law effect in each year. We can see that, as time goes on, the violent crime, murder and robbery rate increases but decreases at the end and number of states having shall law effect also increases.

In state 12 the shall issue law allowing law abiding citizens to carry handguns was enforced in 1988 and we see a considerable decrease in rate of murder after 1989. In state's 38 and 46 the shall carry law was implemented in 1986, and there has not been a significant change in crime, robbery and murder rate after the law enforcement.

We see similar decrease in crime after shall-issue law in state 22 and state 32. We could say that, having shall law in effect increases all malfeasance activities in states, but coming to that conclusion just by looking at descriptive statistics will lead us to misleading effects because we have to account for state level heterogeneity, heteroskedasticity and lot more.

Regression Models:

Now that we have looked at the descriptive statistics we need to need to validate whether the inferences we made from the plots are consistent with outputs of our regression models. For that, we ran several models to draw a conclusion of which model best describes our dataset.

We have plotted histograms of violent crime rate, robbery rate and murder rate to understand their distribution. We can see that all three rates are right skewed, which means their variance is not constant. So, to control for that, we have taken log on all three variables.

Violent Rate:

1. Pooled OLS

regress ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop

```
. do "C:\Users\NXM171~1\AppData\Local\Temp\35\STD3480_000000.tmp"

. regress ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop
```

Source	SS	df	MS			
				Number of obs	=	1,173
				F(8, 1164)	=	188.41
Model	275.712977	8	34.4641221	Prob > F	=	0.0000
Residual	212.918581	1,164	.182919743	R-squared	=	0.5643
				Adj R-squared	=	0.5613
Total	488.631558	1,172	.416921125	Root MSE	=	.42769

ln_vio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
shall	-.3683869	.0325674	-11.31	0.000	-.4322844	-.3044895
incarc_rate	.0016126	.0001072	15.05	0.000	.0014024	.0018229
density	.0266885	.013168	2.03	0.043	.0008527	.0525242
pb1064	.0808526	.0166514	4.86	0.000	.0481825	.1135227
pw1064	.0312005	.0083776	3.72	0.000	.0147636	.0476374
pm1029	.0088709	.0107737	0.82	0.410	-.0122671	.0300089
avginc	.0012051	.0077802	0.15	0.877	-.0140597	.01647
pop	.0427098	.0025588	16.69	0.000	.0376894	.0477303
_cons	2.981738	.5433938	5.49	0.000	1.915598	4.047879

A Pooled OLS with Least Squared Standard Error estimates was run

We choose to not include mur and rob variables as it is reverse causation of violent crime rate and does not add any new significance to explaining the variation in violence crime rate vio.

Results:

- We find that avginc and pm1029 are significant at 10% level of significance (insignificant at 5%)
- Enforcement of shall-issue laws decrease the violent crime rate by 37%, which is not realistic given the enforcement of a single law cannot bring down the violence rate by 37%
- For a 1% increase in population of white the violent crime rate increases by 3.1% and for 1% increase in population of black the violent crime rate increases by 8%

2. **White's test to check for heteroskedasticity in the data**

estat imtest, white

```
. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(43)      =    454.02
         Prob > chi2   =    0.0000

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	454.02	43	0.0000
Skewness	107.86	8	0.0000
Kurtosis	4.22	1	0.0399
Total	566.10	52	0.0000

The variance of an explanatory variable increases the variance of the error term increases.

Implications

1. Least square estimators are no longer best estimators although unbiased and consistent
2. The standard errors are incorrect hence incorrect confidence interval and hypothesis testing

Results:

H0: There is not heteroskedasticity in the data

H1: There exists heteroskedasticity in the data

1. Based on the estimates of the White's test, we see that the p-value 0.000 is less than 0.05. Hence, we reject the null hypothesis and conclude there exists heteroskedasticity in the data.

3. **Pooled OLS with clustered robust errors**

In order the remove the heteroskedasticity in the pooled OLS, White's robust standard errors is used

regress ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, vce(cluster stateid)

```
. regress ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, vce(cluster stateid)

Linear regression                               Number of obs     =      1,173
                                                F(8, 50)          =      62.13
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5643
                                                Root MSE          =     .42769

                                (Std. Err. adjusted for 51 clusters in stateid)
```

ln_vio	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
shall	-.3683869	.113937	-3.23	0.002	-.5972361	-.1395378
incarc_rate	.0016126	.0005999	2.69	0.010	.0004076	.0028177
density	.0266885	.0414909	0.64	0.523	-.0566485	.1100255
pb1064	.0808526	.0713875	1.13	0.263	-.0625334	.2242386
pw1064	.0312005	.03409	0.92	0.364	-.0372713	.0996723
pm1029	.0088709	.0340964	0.26	0.796	-.0596137	.0773554
avginc	.0012051	.0240808	0.05	0.960	-.0471626	.0495728
pop	.0427098	.011729	3.64	0.001	.0191515	.0662681
_cons	2.981738	2.166513	1.38	0.175	-1.369831	7.333307

Comparison of Standard error estimates between Pooled OLS with standard errors vs Pooled OLS with Clustered robust standard errors:

Pooled OLS with standard errors

ln_vio	Coef.	Std. Err.	t	P>|t|
shall	-.3683869	.0325674	-11.31	0.000
incarc_rate	.0016126	.0001072	15.05	0.000
density	.0266885	.013168	2.03	0.043
pb1064	.0808526	.0166514	4.86	0.000
pw1064	.0312005	.0083776	3.72	0.000
pm1029	.0088709	.0107737	0.82	0.410
avginc	.0012051	.0077802	0.15	0.877
pop	.0427098	.0025588	16.69	0.000
_cons	2.981738	.5433938	5.49	0.000

Pooled OLS with Robust standard errors

ln_vio	Coef.	Robust Std. Err.	t	P>|t|
shall	-.3683869	.113937	-3.23	0.002
incarc_rate	.0016126	.0005999	2.69	0.010
density	.0266885	.0414909	0.64	0.523
pb1064	.0808526	.0713875	1.13	0.263
pw1064	.0312005	.03409	0.92	0.364
pm1029	.0088709	.0340964	0.26	0.796
avginc	.0012051	.0240808	0.05	0.960
pop	.0427098	.011729	3.64	0.001
_cons	2.981738	2.166513	1.38	0.175

Results:

1. There is a significant different between the standard errors and Clustered robust standard errors. The characteristics associated with violence rate are not captured by the independent variables. There ignoring autocorrelation results in results of pooled OLS is overstated
2. The variables shall, incarc_rate & pop are significant at 5%
3. Pooled OLS does not allow us to control unobserved heterogeneity. Hence, we use the Fixed Effects model

4. **Panel Regression: Entity Fixed effects**

xtset stateid

xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, fe vce(cluster stateid)

estimates store fixed

```
. xtset stateid
       panel variable:  stateid (balanced)

.
. xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, fe vce(cluster stateid)

Fixed-effects (within) regression               Number of obs     =      1,173
Group variable: stateid                         Number of groups  =         51

R-sq:                                           Obs per group:
     within  = 0.2178                                         min =         23
     between = 0.0033                                         avg =       23.0
     overall = 0.0001                                         max =         23

                                                F(8,50)           =      34.10
corr(u_i, Xb)  = -0.3687                        Prob > F          =     0.0000

                                (Std. Err. adjusted for 51 clusters in stateid)
```

ln_vio	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
shall	-.0461415	.0417616	-1.10	0.275	-.1300223	.0377392
incarc_rate	-.000071	.0002504	-0.28	0.778	-.0005739	.0004318
density	-.1722901	.1376129	-1.25	0.216	-.4486936	.1041135
pb1064	.1042804	.0326849	3.19	0.002	.0386308	.1699301
pw1064	.0408611	.0134585	3.04	0.004	.0138289	.0678932
pm1029	-.0502725	.0206949	-2.43	0.019	-.0918394	-.0087057
avginc	-.0092037	.0129649	-0.71	0.481	-.0352445	.016837
pop	.0115247	.014224	0.81	0.422	-.0170452	.0400945
_cons	3.866017	.7701057	5.02	0.000	2.319214	5.412819
sigma_u	.68024951					
sigma_e	.16072287					
rho	.94712779	(fraction of variance due to u_i)				

Results:

1. Ignoring heteroskedasticity in the data does lead to overestimating the coefficients of the model.
2. From the model, most of the variables are insignificant at 5% SI.
3. One of the disadvantages of the fixed effects model is that it does not capture the effects of time invariant variables and slow changing variables. Hence, we should try and run a fixed effects model with both time and entity.

5. **Fixed effects – Time and Cross Sections**

xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop i.year, fe vce(robust)

```
. testparm i.year

 ( 1)   78.year = 0
 ( 2)   79.year = 0
 ( 3)   80.year = 0
 ( 4)   81.year = 0
 ( 5)   82.year = 0
 ( 6)   83.year = 0
 ( 7)   84.year = 0
 ( 8)   85.year = 0
 ( 9)   86.year = 0
 (10)   87.year = 0
 (11)   88.year = 0
 (12)   89.year = 0
 (13)   90.year = 0
 (14)   91.year = 0
 (15)   92.year = 0
 (16)   93.year = 0
 (17)   94.year = 0
 (18)   95.year = 0
 (19)   96.year = 0
 (20)   97.year = 0
 (21)   98.year = 0
 (22)   99.year = 0

        F( 22,     50) =   21.62
             Prob > F =    0.0000
```

Testing for strength of Time variables

H0: Time effects are insignificant

H1: Time effects are significant

Here the p-value of the model is 0.00, which is less than 005 at 5% SI. Hence, we can conclude that Time effects are significant.

```
. xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop i.year, fe vce(robust)

Fixed-effects (within) regression               Number of obs     =      1,173
Group variable: stateid                         Number of groups  =         51

R-sq:                                           Obs per group:
     within  = 0.4180                                         min =         23
     between = 0.0419                                         avg =       23.0
     overall = 0.0009                                         max =         23

                                                F(30,50)          =      56.86
corr(u_i, Xb)  = -0.2929                        Prob > F          =     0.0000

                               (Std. Err. adjusted for 51 clusters in stateid)
------------------------------------------------------------------------------
             |               Robust
      ln_vio |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |  -.0279935   .0407168    -0.69   0.495    -.1097757    .0537886
 incarc_rate |    .000076   .0002079     0.37   0.716    -.0003416    .0004935
     density |   -.091555   .1238622    -0.74   0.463    -.3403396    .1572296
      pb1064 |   .0291862   .0495407     0.59   0.558    -.0703192    .1286916
      pw1064 |   .0092501   .0237564     0.39   0.699    -.0384659    .0569662
      pm1029 |   .0733254   .0524733     1.40   0.168    -.0320704    .1787211
      avginc |   .0009587   .0164931     0.06   0.954    -.0321688    .0340861
         pop |  -.0047544   .0152294    -0.31   0.756    -.0353436    .0258347
             |
        year |
         78  |   .0585261   .0161556     3.62   0.001     .0260767    .0909755
         79  |   .1639486   .0244579     6.70   0.000     .1148233    .2130738
         80  |   .2170759   .0334184     6.50   0.000     .1499531    .2841987
         81  |   .2172551   .0391956     5.54   0.000     .1385284    .2959819
         82  |   .1946328   .0465743     4.18   0.000     .1010856      .28818
         83  |    .158645   .0593845     2.67   0.010     .0393676    .2779223
         84  |   .1929883   .0770021     2.51   0.015     .0383251    .3476515
         85  |   .2444764   .0922217     2.65   0.011     .0592438    .4297091
         86  |   .3240904   .1089181     2.98   0.004     .1053219    .5428589
         87  |    .324365   .1249881     2.60   0.012      .073319    .5754111
         88  |   .3867412   .1397074     2.77   0.008     .1061305    .6673518
         89  |   .4422143   .1535358     2.88   0.006     .1338286    .7505999
         90  |   .5430478   .1960859     2.77   0.008     .1491976     .936898
         91  |   .5959456   .2040685     2.92   0.005     .1860618    1.005829
         92  |   .6275171   .2170306     2.89   0.006     .1915982    1.063436
         93  |   .6497414   .2246177     2.89   0.006     .1985834    1.100899
         94  |   .6354187   .2332437     2.72   0.009     .1669349    1.103903
         95  |   .6276831   .2423607     2.59   0.013     .1408874    1.114479
         96  |   .5713423   .2534067     2.25   0.029       .06236    1.080325
         97  |   .5501153   .2613516     2.10   0.040     .0251751    1.075055
         98  |   .4932904   .2746546     1.80   0.079    -.0583697     1.04495
         99  |   .4328776   .2862197     1.51   0.137    -.1420117    1.007767
             |
       _cons |   3.765525   1.152108     3.27   0.002     1.451448    6.079603
-------------+----------------------------------------------------------------
     sigma_u |  .6663043
     sigma_e |  .1400264
         rho |  .95770338   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Results:

1. The time significant variables are significant. However, most of the other independent variables are insignificant.

6. Random effects

The data provided is the entire data set between the years 1977-1999. Hence, it is not possible to run a random effects model on this data. But for the sake of the analysis, we are running a random effects model

xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, re vce(cluster stateid)

```
. xtreg ln_vio shall incarc_rate density pb1064 pw1064 pm1029 avginc pop, re vce(cluster stateid)

Random-effects GLS regression                   Number of obs     =      1,173
Group variable: stateid                         Number of groups  =         51

R-sq:                                           Obs per group:
     within  = 0.2044                                         min =         23
     between = 0.4908                                         avg =       23.0
     overall = 0.4591                                         max =         23

                                                Wald chi2(8)      =     167.14
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

                               (Std. Err. adjusted for 51 clusters in stateid)
------------------------------------------------------------------------------
             |               Robust
      ln_vio |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       shall |   -.069609    .038845    -1.79   0.073    -.1457438    .0065258
 incarc_rate |   .0001888   .0001877     1.01   0.314    -.0001791    .0005567
     density |   .0661588   .0437925     1.51   0.131    -.0196729    .1519905
      pb1064 |   .1067022   .0270973     3.94   0.000     .0535924    .1598119
      pw1064 |   .0400716   .0127282     3.15   0.002     .0151248    .0650184
      pm1029 |  -.0375292   .0180436    -2.08   0.038     -.072894   -.0021643
      avginc |  -.0105112   .0117802    -0.89   0.372    -.0335999    .0125775
         pop |   .0225755   .0116369     1.94   0.052    -.0002323    .0453833
       _cons |   3.525463   .7786851     4.53   0.000     1.999268    5.051658
-------------+----------------------------------------------------------------
     sigma_u |  .33790775
     sigma_e |  .16072287
         rho |  .81550462   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

7. Hausman test:

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
       shall |   -.0461415     -.069609        .0234675               .
 incarc_rate |    -.000071     .0001888       -.0002598        .0000635
     density |   -.1722901     .0661588       -.2384489        .0763882
      pb1064 |    .1042804     .1067022       -.0024217         .011767
      pw1064 |    .0408611     .0400716        .0007895               .
      pm1029 |   -.0502725    -.0375292       -.0127434        .0021099
      avginc |   -.0092037    -.0105112        .0013075        .0006269
         pop |    .0115247     .0225755       -.0110508        .0059821
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       31.86
                Prob>chi2 =      0.0001
                (V_b-V_B is not positive definite)
```

Hypothesis Testing:

H0: There is no endogeneity in the data, hence we can run random effects model.

H1: There is endogeneity in the data, hence, we need to run fixed effects model.

Results:

The results are synonymous with our expectation that we cannot run random effects model on this entire dataset.

Robbery Rate:

POOLED OLS MODEL:

1. **Pooled OLS model for robbery rate against "shall" law alone**:

We have observed that variable rob is right skewed, so we performed log on variable 'rob'. On taking log for the 'rob' variable our variable is now approximately normally distributed. We run the pooled OLS model.

Code: POLS_rob <- plm(lnrob~shall, data=datag, model = "pooling", index = c("stateid","year"))
> summary(POLS_rob)

```
Call:
plm(formula = lnrob ~ shall, data = datag, model = "pooling",
    index = c("stateid", "year"))

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

Residuals :
     Min.   1st Qu.    Median   3rd Qu.      Max.
-3.016753 -0.521484  0.054927  0.612161  2.526408

Coefficients :
             Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  4.873051   0.030050 162.163 < 2.2e-16 ***
shall       -0.773321   0.060964 -12.685 < 2.2e-16 ***
---
```

Analysis:

- Coefficient on "Shall" is highly significant (1% significance level), with an estimate of "-0.77332". It can be interpreted that if "shall" law is introduced, robbery rate reduces by 77.3%.
- This is huge impact, but we haven't included any other variables in this model.

2. **Pooled OLS model for robbery rate against all variables:**

Code: > POLS_rob2 <- plm(lnrob~incarc_rate+pb1064+pw1064+pm1029+pop+avginc+density+shall, data=datag, model = "pooling", index = c("stateid","year"))
> summary(POLS_rob2)

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

Residuals :
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.350140 -0.359929  0.082074  0.445931  1.531312

Coefficients :
              Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)  0.9041383  0.7733572   1.1691 0.2425994
incarc_rate  0.0010057  0.0001525   6.5949 6.444e-11 ***
pb1064       0.1021882  0.0236982   4.3121 1.754e-05 ***
pw1064       0.0275209  0.0119230   2.3082 0.0211614 *
pm1029       0.0272565  0.0153331   1.7776 0.0757264 .
pop          0.0778177  0.0036417  21.3684 < 2.2e-16 ***
avginc       0.0407325  0.0110728   3.6786 0.0002452 ***
density      0.0905048  0.0187408   4.8293 1.553e-06 ***
shall       -0.5288202  0.0463499 -11.4093 < 2.2e-16 ***
---
```

White Test:

```
> coeftest(POLS_rob2, vcov. = vcovHC(POLS_rob2,type="HC0",cluster="group"))

t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
(Intercept)  0.9041383  3.0209728  0.2993 0.7647744
incarc_rate  0.0010057  0.0006316  1.5924 0.1115744
pb1064       0.1021882  0.0882240  1.1583 0.2469873
pw1064       0.0275209  0.0444130  0.6197 0.5356043
pm1029       0.0272565  0.0411731  0.6620 0.5081039
pop          0.0778177  0.0222213  3.5019 0.0004794 ***
avginc       0.0407325  0.0277840  1.4660 0.1429077
density      0.0905048  0.0453710  1.9948 0.0463005 *
shall       -0.5288202  0.1587469 -3.3312 0.0008918 ***
```

3.Pooled OLS model for robbery rate against all variables with logarithmic terms:

```
> POLS_rob2 <- plm(lnrob~lnincarc_rate+lnpb1064+pw1064+pm1029+lnpop+lnavginc+lndensity+shall, data=datag, model = "pooling", index = c("stateid","year"))
> summary(POLS_rob2)
Pooling Model

Call:
plm(formula = lnrob ~ lnincarc_rate + lnpb1064 + pw1064 + pm1029 + 
    lnpop + lnavginc + lndensity + shall, data = datag, model = "pooling", 
    index = c("stateid", "year"))

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

Residuals :
     Min.   1st Qu.    Median   3rd Qu.      Max. 
-1.478572 -0.277269 -0.011166  0.296851  1.614357 

Coefficients :
                Estimate Std. Error t-value  Pr(>|t|)    
(Intercept)   -3.6283894  0.4756608 -7.6281 4.934e-14 ***
lnincarc_rate  0.4010048  0.0365320 10.9768 < 2.2e-16 ***
lnpb1064       0.3288989  0.0414020  7.9440 4.587e-15 ***
pw1064         0.0083744  0.0032740  2.5578   0.01066 *  
pm1029         0.1605866  0.0122932 13.0630 < 2.2e-16 ***
lnpop          0.2748983  0.0187784 14.6390 < 2.2e-16 ***
lnavginc       1.1245734  0.0983859 11.4302 < 2.2e-16 ***
lndensity      0.1847102  0.0124336 14.8558 < 2.2e-16 ***
shall         -0.2814399  0.0358072 -7.8599 8.708e-15 ***
```

White Test:

```
> coeftest(POLS_rob2, vcov. = vcovHC(POLS_rob2,type="HC0",cluster="group"))

t test of coefficients:

                Estimate Std. Error t value  Pr(>|t|)    
(Intercept)   -3.6283894  1.7831290 -2.0348 0.0420928 *  
lnincarc_rate  0.4010048  0.1578236  2.5408 0.0111876 *  
lnpb1064       0.3288989  0.1424906  2.3082 0.0211618 *  
pw1064         0.0083744  0.0112906  0.7417 0.4584092    
pm1029         0.1605866  0.0387436  4.1449 3.647e-05 ***
lnpop          0.2748983  0.0673878  4.0793 4.824e-05 ***
lnavginc       1.1245734  0.2800491  4.0156 6.308e-05 ***
lndensity      0.1847102  0.0375761  4.9156 1.012e-06 ***
shall         -0.2814399  0.0783108 -3.5939 0.0003394 ***
---
```

Residual Sum of Squares: 257.67
R-Squared: 0.75874
Adj. R-Squared: 0.75708
F-statistic: 457.589 on 8 and 1164 DF, p-value: < 2.22e-16

- We observed that, Adj. R-Squared value has increased from POLS_rob3 (0.59343) to POLS_rob2 (0.75708) and more number of variables are significant in POLS_rob2.
- So, the model POLS_rob2 better explains the variability in dependent variable in terms of independent variables.
- “shall” law is highly significant with a coefficient estimate “-0.2814399”. It can be inferred that, introducing the “shall” law reduces the robbery rate by 28.15. This is big number, but this estimate magnitude dropped significantly from the model POLS_rob1. This is because, shall law variable in model POLS_rob1 is overestimating the effects of other omitted variables.
- All the other variables, except “pw1064” are significant. And all these variables are positively correlated with the robbery rate.
- But Pooled OLS model will not avoid the problem of observed and unobserved heterogeneity. Which means POLS model will not take state specific variables (Observed and unobserved) into the consideration. Like, cultural attitude of people towards robbery, effectiveness of crime prevention departments etc. This cause endogeneity in the model, which is why shall law might got high estimate value.
- We can avoid heterogeneity by using “Fixed Effects” model.

ENTITY FIXED EFFECT:

```
> EFE_rob1 <- plm(lnrob~lnincarc_rate+lnpb1064+pw1064+pm1029+lnpop+lnavginc+lndensity+shall, data=datag, model = "within", index = c("stateid","year"))
> coeftest(EFE_rob1, vcov. = vcovHC(EFE_rob1,type="HC0",cluster="group"))

t test of coefficients:

               Estimate Std. Error t value Pr(>|t|)
lnincarc_rate -0.1309037  0.0896032 -1.4609  0.14432
lnpb1064      -0.4517934  0.2514141 -1.7970  0.07261 .
pw1064         0.0107922  0.0145132  0.7436  0.45727
pm1029        -0.0146667  0.0317735 -0.4616  0.64446
lnpop         -4.5355223  4.7318070 -0.9585  0.33801
lnavginc       0.4018976  0.3077423  1.3060  0.19184
lndensity      4.8757127  4.7346585  1.0298  0.30333
shall          0.0083804  0.0531299  0.1577  0.87469
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- In the above model, only "lnpb1064" came out to be significant and it's only at 10% significance level. Shall law is not statistically significant even at 10% significance level but it has +ve sign. Let's try this modelling on non-transformed variables.

Log-Linear Model:

```
> EFE_rob2 <- plm(lnrob~incarc_rate+pb1064+pw1064+pm1029+pop+avginc+density+shall, data=datag, model = "within", index = c("stateid","year"))
> coeftest(EFE_rob2, vcov. = vcovHC(EFE_rob2,type="HC0",cluster="group"))

t test of coefficients:

              Estimate  Std. Error t value Pr(>|t|)
incarc_rate -7.6342e-05  3.1677e-04 -0.2410  0.80960
pb1064       1.1154e-01  5.0477e-02  2.2097  0.02733 *
pw1064       2.7181e-02  1.6217e-02  1.6761  0.09400 .
pm1029       1.1182e-02  2.8712e-02  0.3894  0.69703
pop          1.6333e-02  2.7222e-02  0.6000  0.54863
avginc      -1.7519e-02  2.1743e-02 -0.8057  0.42057
density     -1.8609e-01  1.6414e-01 -1.1337  0.25715
shall       -7.8190e-03  5.4435e-02 -0.1436  0.88581
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- In this model, pb1064 is significant at 5% significance level and pw1064 is significant at 10% significance level. Both estimates are positive. They infer that increase in black population or white population who are aged between 10 to 64 years, the robbery rate increases.
- Shall law has negative sign and the magnitude of estimate is very low, but the estimate is not significant even at 10% significance level.
- We can infer that shall law has no effect on the robbery rate.
- But Entity Fixed Effects model couldn't control any omitted variable which is constant across the states but changes over time. To avoid this problem, we should run the model using Entity and Time Fixed Effects model.

ENTITY AND TIME FIXED MODEL:

Code: ETFE_rob1 <- plm(lnrob~incarc_rate+pb1064+pw1064+pm1029+pop+avginc+density+shall+factor(year), data=datag, model = "within", index = c("stateid","year"))

summary(ETFE_rob1)

Summary:

```
# t test of coefficients:
#
#                  Estimate  Std. Error t value  Pr(>|t|)
# incarc_rate     3.1370e-05  3.3981e-04  0.0923 0.9264657
# pb1064          1.4108e-02  8.2161e-02  0.1717 0.8636976
# pw1064         -1.2832e-02  3.2022e-02 -0.4007 0.6886949
# pm1029          1.0461e-01  7.1347e-02  1.4661 0.1428955
# pop             1.6376e-05  2.5351e-02  0.0006 0.9994847
# avginc          1.4357e-02  2.4208e-02  0.5931 0.5532574
# density        -4.4745e-02  1.9373e-01 -0.2310 0.8173851
# shall           2.6830e-02  5.0996e-02  0.5261 0.5989144
# factor(year)78  3.2850e-02  2.1199e-02  1.5496 0.1215368
# factor(year)79  1.3759e-01  3.1391e-02  4.3832 1.282e-05 ***
# factor(year)80  2.4341e-01  4.4436e-02  5.4777 5.347e-08 ***
# factor(year)81  2.7371e-01  4.9729e-02  5.5040 4.626e-08 ***
# factor(year)82  2.1599e-01  6.2955e-02  3.4309 0.0006242 ***
# factor(year)83  1.2082e-01  8.4747e-02  1.4256 0.1542648
# factor(year)84  7.8831e-02  1.0402e-01  0.7578 0.4487271
# factor(year)85  1.1315e-01  1.2439e-01  0.9097 0.3631988
# factor(year)86  1.8957e-01  1.4871e-01  1.2748 0.2026549
# factor(year)87  1.5722e-01  1.6507e-01  0.9524 0.3410941
# factor(year)88  1.9276e-01  1.8364e-01  1.0497 0.2940990
# factor(year)89  2.4873e-01  2.0922e-01  1.1889 0.2347520
# factor(year)90  3.5098e-01  2.6083e-01  1.3456 0.1786988
# factor(year)91  4.6685e-01  2.7287e-01  1.7109 0.0873777 .
# factor(year)92  4.6332e-01  2.8845e-01  1.6062 0.1085136
# factor(year)93  4.7970e-01  3.0127e-01  1.5923 0.1116121
# factor(year)94  4.9438e-01  3.1610e-01  1.5640 0.1181119
# factor(year)95  4.9402e-01  3.2630e-01  1.5140 0.1303145
# factor(year)96  4.3416e-01  3.4251e-01  1.2676 0.2052176
# factor(year)97  3.6524e-01  3.5008e-01  1.0433 0.2970343
# factor(year)98  2.6772e-01  3.6070e-01  0.7422 0.4581139
# factor(year)99  1.8947e-01  3.7585e-01  0.5041 0.6142850
```

3.3 Murder Rate:

POOLED OLS MODEL:

1. Y -> Murder rate, X- > “shall” law:

```
plm(formula = lnmur ~ shall, data = datag, model = "pooling",
index = c("stateid", "year"))

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

Residuals :
Min.  1st Qu.   Median  3rd Qu.     Max.
-3.03362 -0.48657  0.10187  0.46289  2.49194

Coefficients :
Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  1.897556   0.022609  83.928 < 2.2e-16 ***
shall       -0.473372   0.045869 -10.320 < 2.2e-16 ***
---
```

Y -> Murder rate, X- > shall, lnincarc_rate, lnpb1064,pm1029,pw1064, lndensity, lnavginc, lnpop, shall

```
plm(formula = lnmur ~ lnincarc_rate + lnpb1064 + pw1064 + pm1029 +
    lnavginc + lnpop + lndensity + shall, data = datag, model = "pooling",
    index = c("stateid", "year"))

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

Residuals :
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.178655 -0.252239  0.032139  0.258513  1.307631

Coefficients :
                 Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)   -3.19673561  0.40981428 -7.8004 1.364e-14 ***
lnincarc_rate  0.63429404  0.03147482 20.1524 < 2.2e-16 ***
lnpb1064       0.20242577  0.03567066  5.6749 1.751e-08 ***
pw1064        -0.00082902  0.00282081 -0.2939    0.7689
pm1029         0.16539198  0.01059147 15.6156 < 2.2e-16 ***
lnavginc      -0.42629663  0.08476619 -5.0291 5.703e-07 ***
lnpop          0.10265977  0.01617891  6.3453 3.173e-10 ***
lndensity      0.06393792  0.01071236  5.9686 3.172e-09 ***
shall         -0.13726169  0.03085031 -4.4493 9.441e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> coeftest(pooling_var, vcov. = vcovHC(pooling_var, type = 'HC0', cluster = 'group'))

t test of coefficients:

                 Estimate  Std. Error t value  Pr(>|t|)
(Intercept)   -3.19673561  1.77934414 -1.7966   0.07266 .
lnincarc_rate  0.63429404  0.15037829  4.2180 2.656e-05 ***
lnpb1064       0.20242577  0.15088578  1.3416   0.17999
pw1064        -0.00082902  0.01347187 -0.0615   0.95094
pm1029         0.16539198  0.04035862  4.0981 4.455e-05 ***
lnavginc      -0.42629663  0.31805404 -1.3403   0.18040
lnpop          0.10265977  0.06777371  1.5147   0.13011
lndensity      0.06393792  0.04421248  1.4462   0.14840
shall         -0.13726169  0.07524825 -1.8241   0.06839 .
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Analysis:

- Density, Population, is insignificant and pw 1064, pm1029 are significant at 10%, rest all variables are significant at 5% or less.
- Model 1 (pooling model with no other variables) suggests that shall-issue laws reduce the murder rate by 47% compared to model 2(pooling model with other variables) suggests that shall-issue laws reduce the murder rate by 13.7%. Shall law in model 2 is significant at 10%.
- The reason for the huge coefficient shift of shall from model 1 to model 2 because of omitted variable bias. In model 1 “shall” variable took the effects of omitted variables which are highly correlated with it. So, the coefficient of shall in model1 is biased and inconsistent. We cannot be sure that coefficient in model 2 gives us the correct estimate because in pooled OLS we can cannot account or control for unobserved heterogeneity, which makes the estimate biased and inconsistent.

ENTITY FIXED EFFECT:

The coefficients for Model 3 are:

```
> coeftest(within_model, vcov. = vcovHC(within_model, type = 'HC0', cluster = 'group'))

t test of coefficients:

               Estimate Std. Error t value Pr(>|t|)   
lnincarc_rate -0.172066   0.060793 -2.8304 0.004733 **
pb1064         0.046569   0.065853  0.7072 0.479610   
pw1064         0.016808   0.013178  1.2754 0.202425   
pm1029         0.016707   0.019933  0.8381 0.402127   
avginc         0.027525   0.016669  1.6513 0.098966 . 
density       -0.492895   0.152529 -3.2315 0.001268 **
shall         -0.068834   0.038547 -1.7857 0.074422 . 
pop           -0.029254   0.023743 -1.2321 0.218170   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

- After adding entity fixed effects which controls for unobserved heterogeneity, we see a huge drop in the effect of shall on murder rate. Now, Shall-laws in states reduce the murder rate by 6.8% compared to 31.31% in model 2, and Shall in model3 is significant at 10%.
- This huge drop in shall-issue on murder rate confirms an important reason mentioned above i.e. Omitted variable bias in the model2 which did not control for unobserved heterogeneity. Also, effect of shall issue laws on the murder rate is no longer statistically significant.

- The regression model with fixed effects is more reasonable because this controls for unobserved characteristics that vary between states but are constant over time.

ENTITY AND TIME FIXED EFFECT:

```
coeftest(FE_withtime, vcov. = vcovHC(FE_withtime, type = 'HC0', cluster = 'group'))

t test of coefficients:

                  Estimate  Std. Error t value  Pr(>|t|)
lnincarc_rate  -0.09427130  0.05888997 -1.6008 0.1097096
pb1064          0.01991858  0.07831166  0.2544 0.7992730
pw1064         -0.00073305  0.02193523 -0.0334 0.9733466
pm1029          0.07005678  0.04315377  1.6234 0.1047878
avginc          0.05658911  0.01559650  3.6283 0.0002985 ***
density        -0.49010721  0.13991140 -3.5030 0.0004787 ***
pop            -0.03423410  0.02269031 -1.5088 0.1316509
shall          -0.02211793  0.03945705 -0.5606 0.5752145
factor(year)78  0.00281992  0.03182859  0.0886 0.9294183
factor(year)79  0.06928101  0.02939144  2.3572 0.0185899 *
factor(year)80  0.10282729  0.04140624  2.4834 0.0131636 *
factor(year)81  0.11831445  0.04915389  2.4070 0.0162484 *
factor(year)82  0.04819185  0.05822813  0.8276 0.4080560
factor(year)83  0.00311935  0.06509093  0.0479 0.9617864
factor(year)84 -0.09691006  0.07257494 -1.3353 0.1820531
factor(year)85 -0.04378206  0.08698817 -0.5033 0.6148475
factor(year)86  0.03592244  0.09281725  0.3870 0.6988143
factor(year)87  0.02387782  0.10106112  0.2363 0.8132666
factor(year)88  0.03979493  0.12152242  0.3275 0.7433753
factor(year)89  0.04702005  0.13874587  0.3389 0.7347552
factor(year)90  0.12993939  0.17593594  0.7386 0.4603324
factor(year)91  0.18016115  0.18580563  0.9696 0.3324499
factor(year)92  0.14718859  0.19456008  0.7565 0.4495007
factor(year)93  0.23671715  0.20034685  1.1815 0.2376469
factor(year)94  0.12929227  0.21348205  0.6056 0.5448828
factor(year)95  0.14544388  0.21352082  0.6812 0.4959086
factor(year)96  0.07910954  0.22435847  0.3526 0.7244539
factor(year)97 -0.02347269  0.23087309 -0.1017 0.9190379
factor(year)98 -0.08387386  0.24265682 -0.3456 0.7296738
factor(year)99 -0.15036895  0.24876482 -0.6045 0.5456619
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

- But Entity Fixed Effects model couldn’t control any omitted variable which is constant across the entities but changes over time. To avoid this problem, we should run the model using Entity and Time Fixed Effects model.

- After adding time fixed effects, Shall-issue laws further reduce the murder rate by 2.2% compared to 6.8% in Entity Effects model . But, the effect of shall issue laws in states on the murder rate in Fixed effects with entity and time effects is not statistically significant.

- All variables are coming out to be insignificant in case of time fixed effects except average income and density.

RANDOM EFFECTS MODEL:

random_model <- plm (lnmur ~ lnincarc_rate + pb1064 + pw1064 + pm1029 + avginc + density +shall+ pop, model="random",index=c("stateid","year"),data=datag)

```
> phtest(within_model, random_model)

        Hausman Test

data:  lnmur ~ lnincarc_rate + pb1064 + pw1064 + pm1029 + avginc + density +  ...
chisq = 2254.6, df = 8, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

- As the sample is not randomly selected so it does not make sense to perform random effects on this dataset. Therefore, we opt out of the random effects model.
- Looking at the output of Hausman test (p-value < 0.05), we can say that there is endogeneity present in random effects model. So, we use Fixed effects for this dataset.

In Pooled OLS model, it does not account for fixed effects of states and time effects. To control the unobserved heterogeneity such as cultural attitude, alcoholism and crime prevention programs we move to Entity and Time Fixed Effect models. The estimated parameters of shall-issue laws in pooling method shows a large effect on crime rates be it Violent crime rate, Murder rate or robbery rate. However, this effect is due to omitted variable bias. Because the effect disappears when state and time effects are added.

Limitations of entity and Time fixed effect models:

There might be unobserved heterogeneity in the regression model that vary between states and over time. For example, other strategies that are related to the of shall issue laws implementation and that affect violent crime rates, murder rate and robbery rate. There is a serious risk of simultaneous causality bias. On one hand, increased incarceration reduces violent rate. On the other hand, if violent rate goes up and the police do their job, there will be more prisoners. If there are many violent crimes this may force government to change shall-issue laws.

Conclusion:

The most sensible results include both state fixed effects and time fixed effects that accounts for omitted variable bias, unobserved heterogeneity and time effects. We conclude based on the above results and interpretations that there is no significant effect of shall-issue laws on the violent crime rate, the robbery rate nor on the murder rate. Right to carry laws may be implemented in states that had a percentage growth in states that have had a recent growth in crime and where other attempts to reduce crime have simultaneously been instituted (for example, increased police hiring or higher arrest rates). Also, Incarceration Rate acts as a proxy for the level of expected punishment so we can remove these endogeneity by introducing Instrumental variables in the model like state wise laws related to concealed weapon laws.