Final Project

Applied Econometrics and Time Series Analysis

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Introduction

The purpose of this project is to establish whether shall laws (right to carry handguns) reduce crimes in US or not. The intention is to identify the relation between variables and thereby choose a regression model that fits the data perfectly. This report will provide a walkthrough of our understanding of the dataset provided and motivations for choosing the appropriate regression to model the given panel dataset.

Guns data is a balanced panel dataset which consists of data on 23 years (1977 – 1991) and 51 states (50 US states plus District of Columbia). It consists of a total of 23 X 51 = 1173 observations. There are 13 variables (including state and year) in the data. The variable "shall" is a dummy variable with 0 and 1 indicating the presence or absence of the shall-carry law in effect that year.

A Shall-issue law is one that requires that governments issue concealed carry handgun permits to any applicant who meets the necessary criteria. It takes the value 1 when the following criteria are met:

• The applicant must be an adult

• Should have no significant criminal record

• No history of mental illness and successfully complete a course in firearms safety training (if required by law).

Percent of state population are separated into three groups - 10-29 years old(male), 10-64 years old(white), and 10-64 years old(black). And we have the data for crime rate for each crime type. We start by looking at the starting few observations of the data

```r
guns <- read.dta("guns.dta")

#Take a took at the dataset
head(guns)

##   year   vio  mur   rob incarc_rate   pb1064   pw1064   pm1029      pop
## 1   77 414.4 14.2  96.8          83 8.384873 55.12291 18.17441 3.780403
## 2   78 419.1 13.3  99.1          94 8.352101 55.14367 17.99408 3.831838
## 3   79 413.3 13.2 109.5         144 8.329575 55.13586 17.83934 3.866248
## 4   80 448.5 13.2 132.1         141 8.408386 54.91259 17.73420 3.900368
## 5   81 470.5 11.9 126.5         149 8.483435 54.92513 17.67372 3.918531
## 6   82 447.7 10.6 112.0         183 8.514000 54.89621 17.51052 3.925229
##     avginc    density stateid shall
## 1 9.563148 0.07455240       1     0
## 2 9.932000 0.07556673       1     0
## 3 9.877028 0.07624532       1     0
## 4 9.541428 0.07682881       1     0
## 5 9.548351 0.07718658       1     0
## 6 9.478919 0.07731851       1     0
```

Fig 1.1 : First few observations of our dataset

We also checked for correlation amongst the variables

```r
round(cor(guns),2)

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

Fig 1.2 : Correlation matrix

We find that the terms violent crime rates, murder rate and robbery rates are correlated so we decide to drop the terms 'rob' and 'mur'.

Check the structure of the dataset

```
> str(guns)
'data.frame':	1173 obs. of  14 variables:
 $ year      : int  77 78 79 80 81 82 83 84 85 86 ...
 $ vio       : num  414 419 413 448 470 ...
 $ mur       : num  14.2 13.3 13.2 13.2 11.9 ...
 $ rob       : num  96.8 99.1 109.5 132.1 126.5 ...
 $ incarc_rate: int  83 94 144 141 149 183 215 243 256 267 ...
 $ pb1064    : num  8.38 8.35 8.33 8.41 8.48 ...
 $ pw1064    : num  55.1 55.1 55.1 54.9 54.9 ...
 $ pm1029    : num  18.2 18 17.8 17.7 17.7 ...
 $ pop       : num  3.78 3.83 3.87 3.9 3.92 ...
 $ avginc    : num  9.56 9.93 9.88 9.54 9.55 ...
 $ density   : num  0.0746 0.0756 0.0762 0.0768 0.0772 ...
 $ stateid   : int  1 1 1 1 1 1 1 1 1 1 ...
 $ shall     : int  0 0 0 0 0 0 0 0 0 0 ...
 $ cluster   : int  2 2 2 2 2 2 2 2 2 1 ...
 - attr(*, "datalabel")= chr ""
 - attr(*, "time.stamp")= chr " 5 Sep 2014 22:29"
 - attr(*, "formats")= chr  "%9.0g" "%9.0g" "%9.0g" "%9.0g" ...
 - attr(*, "types")= int  251 254 254 254 252 254 254 254 254 254 ...
 - attr(*, "val.labels")= chr  "" "" "" "" ...
 - attr(*, "var.labels")= chr  "" "Violent Crime Rate per 100,000 population (BJS)" "Murder
Crime Rate per 100,000 population (BJS)" "Robbery Crime Rate per 100,000 population (BJS)" .
..
 - attr(*, "expansion.fields")=List of 5
  ..$ : chr  "_dta" "ReS_Xij" "@age1019 @age2029 @age3039 @age4049 @age5064 @ageo65"
  ..$ : chr  "_dta" "ReS_str" "1"
  ..$ : chr  "_dta" "ReS_j" "demog"
  ..$ : chr  "_dta" "ReS_ver" "v.2"
  ..$ : chr  "_dta" "ReS_i" "fipsstat year"
 - attr(*, "version")= int 12
```

Fig 1.3 : Data Set Information

Simple Linear Regression

We create 2 new variables: black men and log(vio).

```
blackmen<-pb1064*pm1029
```

```
lnvio<- log(vio)
```

First, we build a simple linear regression.

```
> model1 <-lm(lnvio~incarc_rate+pb1064+pw1064+pm1029+blackmen+ pop+avginc+density+factor(stateid)+shall,data=guns)
> summary(model1)

Call:
lm(formula = lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 +
    blackmen + pop + avginc + density + factor(stateid) + shall,
    data = guns)

Residuals:
     Min       1Q   Median       3Q      Max
-0.60286 -0.09761  0.00908  0.10146  0.54052

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        2.881e+00  4.428e-01   6.507 1.16e-10 ***
incarc_rate       -2.712e-04  9.998e-05  -2.713 0.006780 **
pb1064             2.213e-01  2.829e-02   7.824 1.18e-14 ***
pw1064             4.960e-02  5.281e-03   9.392  < 2e-16 ***
pm1029            -3.337e-02  7.093e-03  -4.705 2.86e-06 ***
blackmen          -3.660e-03  6.939e-04  -5.275 1.60e-07 ***
pop                9.575e-03  8.629e-03   1.110 0.267395
avginc            -1.214e-02  5.865e-03  -2.070 0.038725 *
density           -2.332e-01  8.482e-02  -2.749 0.006078 **
factor(stateid)2   5.124e-02  7.187e-02   0.713 0.475985
factor(stateid)4   4.376e-01  9.535e-02   4.589 4.96e-06 ***
factor(stateid)5  -5.836e-03  6.961e-02  -0.084 0.933206
factor(stateid)6   3.648e-01  2.288e-01   1.594 0.111186
factor(stateid)8   8.848e-02  1.168e-01   0.758 0.448739
factor(stateid)9   1.338e-01  1.402e-01   0.955 0.339939
factor(stateid)10  1.806e-01  7.744e-02   2.332 0.019901 *
factor(stateid)11  2.858e+00  7.707e-01   3.709 0.000219 ***
factor(stateid)12  8.629e-01  1.176e-01   7.339 4.14e-13 ***
factor(stateid)13 -1.847e-02  5.378e-02  -0.343 0.731344
factor(stateid)15 -1.765e+00  2.830e-01  -6.236 6.37e-10 ***
factor(stateid)16 -2.282e-01  1.314e-01  -1.736 0.082778 .
factor(stateid)17  5.232e-01  1.081e-01   4.838 1.50e-06 ***
```

```
factor(stateid)18  7.059e-03  1.169e-01   0.060 0.951871    
factor(stateid)19 -3.408e-01  1.376e-01  -2.478 0.013375 *  
factor(stateid)20  3.604e-02  1.085e-01   0.332 0.739705    
factor(stateid)21 -2.180e-01  1.109e-01  -1.966 0.049542 *  
factor(stateid)22  3.234e-01  5.722e-02   5.652 2.02e-08 ***
factor(stateid)23 -8.483e-01  1.420e-01  -5.972 3.15e-09 ***
factor(stateid)24  3.414e-01  5.944e-02   5.744 1.19e-08 ***
factor(stateid)25  5.362e-01  1.546e-01   3.468 0.000545 ***
factor(stateid)26  3.927e-01  1.019e-01   3.853 0.000123 ***
factor(stateid)27 -3.405e-01  1.315e-01  -2.589 0.009755 ** 
factor(stateid)28 -5.005e-01  7.888e-02  -6.345 3.23e-10 ***
factor(stateid)29  3.345e-01  9.791e-02   3.417 0.000656 ***
factor(stateid)30 -7.749e-01  1.117e-01  -6.937 6.79e-12 ***
factor(stateid)31 -1.929e-01  1.226e-01  -1.574 0.115797    
factor(stateid)32  4.767e-01  9.039e-02   5.274 1.60e-07 ***
factor(stateid)33 -9.958e-01  1.482e-01  -6.717 2.94e-11 ***
factor(stateid)34  2.652e-01  1.280e-01   2.072 0.038508 *  
factor(stateid)35  5.082e-01  7.960e-02   6.385 2.51e-10 ***
factor(stateid)36  5.314e-01  1.454e-01   3.654 0.000270 ***
factor(stateid)37 -8.861e-02  5.431e-02  -1.632 0.103044    
factor(stateid)38 -1.626e+00  1.176e-01 -13.824  < 2e-16 ***
factor(stateid)39  1.791e-02  1.303e-01   0.137 0.890683    
factor(stateid)40  9.061e-02  7.214e-02   1.256 0.209377    
factor(stateid)41  2.525e-01  1.233e-01   2.048 0.040756 *  
factor(stateid)42 -1.080e-01  1.415e-01  -0.763 0.445405    
factor(stateid)44  1.790e-01  1.646e-01   1.087 0.277143    
factor(stateid)45  2.756e-01  5.808e-02   4.744 2.36e-06 ***
factor(stateid)46 -8.093e-01  1.059e-01  -7.640 4.68e-14 ***
factor(stateid)47  1.426e-01  7.354e-02   1.939 0.052760 .  
factor(stateid)48  2.230e-01  1.470e-01   1.517 0.129533    
factor(stateid)49 -6.912e-02  1.208e-01  -0.572 0.567386    
factor(stateid)50 -9.798e-01  1.435e-01  -6.829 1.41e-11 ***
factor(stateid)51 -5.897e-01  6.081e-02  -9.697  < 2e-16 ***

factor(stateid)53  3.933e-02  1.075e-01   0.366 0.714486    
factor(stateid)54 -7.128e-01  1.303e-01  -5.472 5.50e-08 ***
factor(stateid)55 -5.483e-01  1.242e-01  -4.415 1.11e-05 ***
factor(stateid)56 -2.308e-01  1.295e-01  -1.782 0.075022 .  
shall             -4.832e-02  1.865e-02  -2.591 0.009684 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1588 on 1113 degrees of freedom
Multiple R-squared:  0.9425,    Adjusted R-squared:  0.9395 
F-statistic: 309.5 on 59 and 1113 DF,  p-value: < 2.2e-16
```

Fig 2.1: Simple Linear Regression Summary

We need to check if there is heteroscedasticity.

First, we check the residual plots.

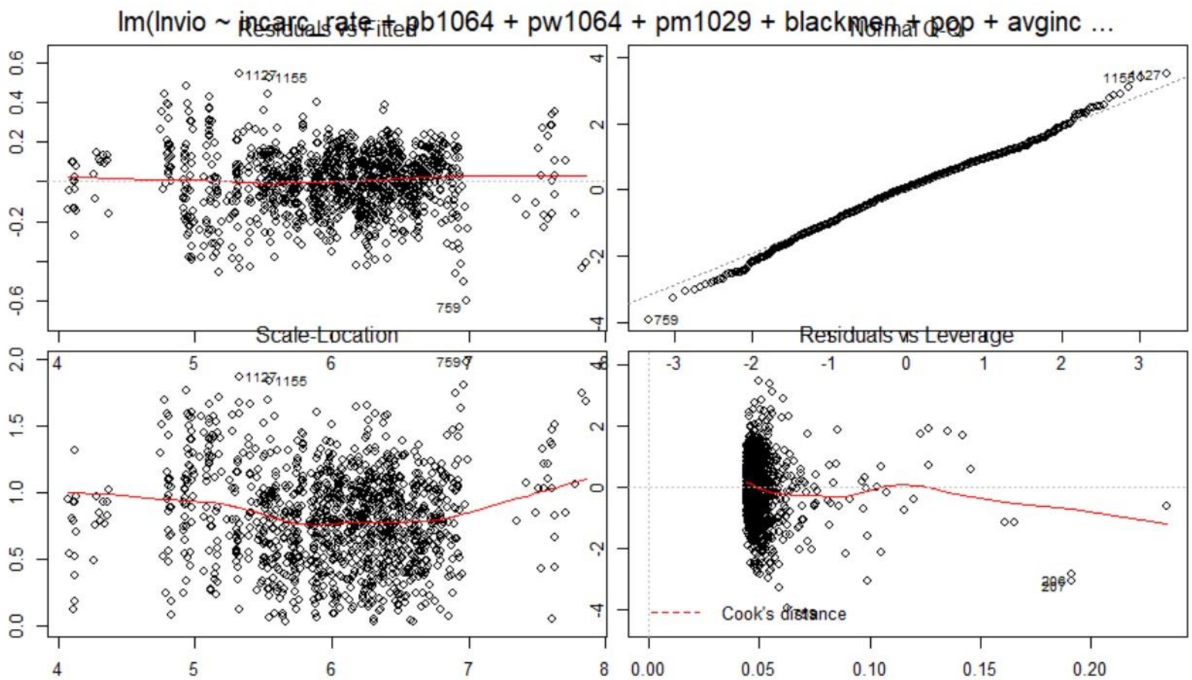

Fig 2.2: Model1 residual plots

From the Residuals plots we doubt that the model suffers from heteroscedasticity because the variance is not very stable.

Second, we verify heteroscedasticity.

```
> bptest(model1)

        studentized Breusch-Pagan test

data:  model1
BP = 326.73, df = 59, p-value < 2.2e-16
```

Fig 2.3: Model1 bptest

All p-value are almost 0, so we reject null hypothesis and conclude that there is heteroscedasticity in the model.

Simple linear model does not work well with panel data.

Pooled OLS

This is panel data, we start with pooled OLS.

```
> model2<-plm(formula =lnvio ~ incarc_rate+pb1064+pw1064+pm1029+blackmen+ pop+avginc+density+shall,
 data = guns, model = "pooling", index = c("stateid","year"))

> summary(model2)
Pooling Model

Call:
plm(formula = lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 +
    blackmen + pop + avginc + density + shall, data = guns, model = "pooling",
    index = c("stateid", "year"))

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

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.66194 -0.27026  0.04990  0.30551  1.04266

Coefficients:
               Estimate  Std. Error  t-value  Pr(>|t|)
(Intercept)  3.46043934  0.59437948   5.8219 7.518e-09 ***
incarc_rate  0.00172464  0.00012112  14.2392 < 2.2e-16 ***
pb1064       0.01983780  0.03508457   0.5654  0.571892
pw1064       0.02644257  0.00870705   3.0369  0.002443 **
pm1029      -0.00190040  0.01206340  -0.1575  0.874851
blackmen     0.00301205  0.00152504   1.9751  0.048497 *
pop          0.04249333  0.00255800  16.6120 < 2.2e-16 ***
avginc       0.00394842  0.00789371   0.5002  0.617030
density      0.02406886  0.01321838   1.8209  0.068885 .
shall       -0.36985819  0.03253545 -11.3679 < 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: 212.21
R-Squared:      0.56571
Adj. R-Squared: 0.56235
F-statistic: 168.327 on 9 and 1163 DF, p-value: < 2.22e-16
```

Fig 3.1: Model2 – Pooled OLS

From the model we see that:

- If the incarceration rate in the state in the previous year increases 1%, the violence rate will increase by 0.17%.
- If the percent of state population that is white, ages 10 to 64, increase 1%, the violence crime rate will increase 2.64%
- Violence crime rate is 0.3% higher for black men.
- If the population increase 1 million, the violence crime rate will increase 4.25%.
- if the state has a shall-carry law in effect in that year, the violence crime rate will decrease by 36.986%. This number may be too large in “real world”. It is suspicious.
- Other variables in the model are not statistically significant.

The reason why we get 36.986% on shall may be Pooled OLS suffer serially correlated errors and heteroskedasticity.

In order to solve the problem, we need to use Cluster Robust Standard Errors to get the correct standard errors.

Pooled OLS with Robust Standard Errors

```
> summary(model2, vcov=vcovHC(model2, method = "arellano"))

Pooling Model

Note: Coefficient variance-covariance matrix supplied: vcovHC(model2, method = "arellano")

Call:
plm(formula = lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 +
    blackmen + pop + avginc + density + shall, data = guns, model = "pooling",
    index = c("stateid", "year"))

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

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.66194 -0.27026  0.04990  0.30551  1.04266

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  3.46043934  2.20013779  1.5728 0.1160305
incarc_rate  0.00172464  0.00053497  3.2238 0.0013002 **
pb1064       0.01983780  0.09110066  0.2178 0.8276567
pw1064       0.02644257  0.03322055  0.7960 0.4262117
pm1029      -0.00190040  0.03957037 -0.0480 0.9617040
blackmen     0.00301205  0.00349380  0.8621 0.3888026
pop          0.04249333  0.01139647  3.7286 0.0002018 ***
avginc       0.00394842  0.02272647  0.1737 0.8621027
density      0.02406886  0.03899376  0.6172 0.5371913
shall       -0.36985819  0.11255312 -3.2861 0.0010463 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 212.21
R-Squared:      0.56571
Adj. R-Squared: 0.56235
F-statistic: 58.047 on 9 and 50 DF, p-value: < 2.22e-16
>
```

Fig 4.1: Pooled OLS with Robust Standard Errors

We see that the coefficients are still the same as the pooled OLS. However, the SE become larger and tvalues become smaller. The large differences of SE between two models imply that the reliability of the pooled OLS estimates is overstated.

We only have 3 significant variables now.

- If the incarceration rate in the state in the previous year increase 1%, the violence crime rate will increase 0.17%.
- If the state population increase 1 million, the violence crime rate will increase 4.25%.
- if the state has a shall-carry law in effect, the violence crime rate will decrease 36.985% (still suspicious)

Pooled OLS may have simultaneous causality bias and unobserved heterogeneity. So we need to use other models to analyze the data set.

Hausman Test

This dataset is not randomly selected from a population (it is a sample of U.S states). So, we would better use fixed effects model.

We use Hausman test to double check if we should Fixed Effects or Random Effects.

Fixed Effects model:

```
> model3<-plm(formula =lnvio ~ incarc_rate+pb1064+pw1064+pm1029+blackmen+ pop+avginc+d
ensity+shall+factor(year), data = guns, model = "within", index = c("stateid","year"))
```

```
> model4<-plm(formula =lnvio ~ incarc_rate+pb1064+pw1064+pm1029+blackmen+ pop+avginc+d
ensity+shall+factor(year), data = guns, model = "between", index = c("stateid","year")
```

```
> phtest(model3,model4)

        Hausman Test

data:  lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 + blackmen + pop +  ...
chisq = 83.391, df = 9, p-value = 3.417e-14
alternative hypothesis: one model is inconsistent
```

Random Effects model:

Fig 5.1: Hausman Test results.

The p-value we got is much smaller than 0.05, hence we can conclude that there is correlation between the error term and the independent variable. Due to the endogeneity we reject the null, we ensure that using fixed effects is the correct model.

Fixed Effect Model

```
Oneway (individual) effect Within Model

Note: Coefficient variance-covariance matrix supplied: vcovHC(model4, method = "arellano")

Call:
plm(formula = lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 +
    blackmen + pop + avginc + density + shall, data = guns, model = "within",
    index = c("stateid"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.6028559 -0.0976112  0.0090839  0.1014598  0.5405242

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
incarc_rate -0.00027119  0.00023942 -1.1327 0.2575827
pb1064       0.22130888  0.06685785  3.3101 0.0009624 ***
pw1064       0.04959890  0.01167296  4.2490 2.326e-05 ***
pm1029      -0.03336986  0.02450153 -1.3619 0.1734893
blackmen    -0.00366032  0.00215343 -1.6998 0.0894551 .
pop          0.00957464  0.01528972  0.6262 0.5313029
avginc      -0.01213753  0.01190243 -1.0198 0.3080674
density     -0.23315156  0.17295632 -1.3480 0.1779207
shall       -0.04832500  0.03979590 -1.2143 0.2248827
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.075
R-Squared:      0.23687
Adj. R-Squared: 0.19642
F-statistic: 43.2118 on 9 and 50 DF, p-value: < 2.22e-16
```

Fig 6.1: Fixed Effects model

From the model we see that:

- If the incarceration rate is insignificant and hence cannot be interpreted.

- If the percent of state population that is black, ages 10 to 64, increase by 1%, the violence crime rate will increase 22.13%
- If the percent of state population that is white, ages 10 to 64, increase by 1%, the violence crime rate will increase 4.95%
- Blackman has a p-value of 0.08 which is insignificant at a 5% significance level but significant at a 10% level. Hence, we cannot interpret its effect.
- Percentage of state population that is male, ages 10 to 29, population, average income and density have a very high p-value > 0.05 and >0.1. Hence, they are insignificant to our model. They do not affect the violence rate.
- The above fixed effects model, has a p-value of 0.224 > 0.05 and a t-value of -1.214 < 1.96 for shall law. Hence, we reject the null to conclude that shall is insignificant. Therefore, we can conclude that the shall law has no effect on the violence.

The reason why we get shall law as insignificant compared to Pooled OLS with Robust Standard Errors may be due to removal of heterogeneity. Previously, the value of shall law was significant and high. This may be due to the effect of some other omitted variable which is highly correlated with shall. This caused shall to be compensating for the variables effect.

Fixed effects model removes the endogeneity and provides for an unbiased and consistent model.

Time & Entity Fixed Effects model

```
Oneway (individual) effect Within Model

Note: Coefficient variance-covariance matrix supplied: vcovHC(model4, method = "arellano")

Call:
plm(formula = lnvio ~ incarc_rate + pb1064 + pw1064 + pm1029 +
    blackmen + pop + avginc + density + shall + factor(year),
    data = guns, model = "within", index = c("stateid", "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4356202 -0.0762597  0.0054355  0.0804917  0.7322541

Coefficients:
                  Estimate  Std. Error t-value  Pr(>|t|)
incarc_rate    -8.8356e-05  1.8873e-04 -0.4682 0.6397701
pb1064          1.8406e-01  7.6074e-02  2.4195 0.0157041 *
pw1064          2.9155e-02  1.9893e-02  1.4656 0.1430459
pm1029          8.2752e-02  4.9199e-02  1.6820 0.0928605 .
blackmen       -4.0522e-03  1.8794e-03 -2.1561 0.0312972 *
pop            -4.4424e-03  1.5825e-02 -0.2807 0.7789704
avginc         -1.6726e-03  1.5134e-02 -0.1105 0.9120177
density        -1.4778e-01  1.3335e-01 -1.1082 0.2680169
shall          -2.9743e-02  3.8666e-02 -0.7692 0.4419327
factor(year)78  5.6203e-02  1.4944e-02  3.7608 0.0001784 ***
factor(year)79  1.5887e-01  2.2825e-02  6.9602 5.854e-12 ***
factor(year)80  2.0504e-01  3.2102e-02  6.3871 2.498e-10 ***
factor(year)81  2.0287e-01  3.7742e-02  5.3751 9.356e-08 ***
factor(year)82  1.8020e-01  4.4049e-02  4.0908 4.614e-05 ***
factor(year)83  1.4710e-01  5.5617e-02  2.6449 0.0082883 **
factor(year)84  1.8357e-01  7.2429e-02  2.5345 0.0114001 *
factor(year)85  2.3610e-01  8.7072e-02  2.7116 0.0068016 **
factor(year)86  3.1776e-01  1.0290e-01  3.0882 0.0020647 **
factor(year)87  3.1823e-01  1.1775e-01  2.7026 0.0069865 **
factor(year)88  3.7926e-01  1.3217e-01  2.8694 0.0041916 **
factor(year)89  4.3396e-01  1.4560e-01  2.9804 0.0029423 **
factor(year)90  4.9576e-01  1.8133e-01  2.7341 0.0063566 **
factor(year)91  5.4479e-01  1.8956e-01  2.8740 0.0041318 **
factor(year)92  5.7306e-01  2.0125e-01  2.8475 0.0044896 **
factor(year)93  5.9118e-01  2.0855e-01  2.8347 0.0046713 **
factor(year)94  5.7402e-01  2.1670e-01  2.6489 0.0081929 **
factor(year)95  5.6320e-01  2.2517e-01  2.5013 0.0125211 *
factor(year)96  5.0210e-01  2.3517e-01  2.1351 0.0329771 *
factor(year)97  4.7669e-01  2.4251e-01  1.9657 0.0495893 *
factor(year)98  4.1706e-01  2.5532e-01  1.6335 0.1026552
factor(year)99  3.5193e-01  2.6617e-01  1.3222 0.1863732
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 20.645
R-Squared:      0.43882
Adj. R-Squared: 0.39715
F-statistic: 64.1431 on 31 and 50 DF, p-value: < 2.22e-16
```

Fig 7.1: Time Fixed Effects model

In the above model we take each year of the panel data as a separate variable to see their individual effects on violence. We see from the p-values that almost all values are significant at a 5% significant level (> 0.05). Thus, we can conclude that the time fixed model is significant.

From the model we see that:

- If the incarceration rate is insignificant and do not have any effect on the violence rate.

- If the percent of state population that is black, ages 10 to 64, increase by 1%, the violence crime rate will increase 18.4%
- The percent of state population that is male, ages 10 to 29, has a p-value of 0.09 which is insignificant at a 5% significance level but significant at a 10% level. Hence, we cannot interpret its effect.
- The violence rate decreases by 0.0405% for black men.
- Percentage of state population that is white, ages 10 to 64, population, average income and density have a very high p-value > 0.05 and >0.1. Hence, they are insignificant to our model. They do not affect the violence rate.
- The above fixed effects model, has a p-value of 0.4419 > 0.05 and a t-value of -0.7692< 1.96 for shall law. Hence, we reject the null to conclude that shall is insignificant. Therefore, we can conclude that the shall law has no effect on the violence.

With the advancing of time, the violence rate has increased. This trend is observed until year 1993 after which the violence rate decreases. This decline is observed until 1997. The effect of year 1998 and 1999 are insignificant to the violence rate.

Conclusion

After observing all models, we can conclude that the Time fixed effects model is the best model. This model was picked as it does not contain any heterogeneity. The model is consistent and unbiased. It also captures the trend in data throughout the years. The values of coefficients have also lowered.

Our model could have predicted better given greater number of rows. This would have allowed more efficiency to the model as the predicted values would be closer to the actual value.

Our selected model shows that the shall law is insignificant. Thereby, we can conclude that there is no effect of shall law on the violence rate throughout the years throughout the states.