# The Effectiveness of Shall Law in the United States

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## ABSTRACT

This Study Investigates the effects of gun control law and incarceration rates on the crime rates of 50 US states plus District of Columbia during the period from 1977 to 1999. For this study, we have classified the crimes into three categories namely

- Crimes involving Violence
- Crimes involving robbery
- Crimes involving murders

This classification will aid our analysis, as the variables we include can have a different impact on these three types of crimes due to different nature of the crimes.

The Variables we included to perform our analysis includes shall-carry law, incarceration rate in previous year, population density, average income, population, state wise population, percentage of males between age of 10 to 29, state wise population percentage of white between age 10 to 64, state wise population percentage of black between age 10 to 64.

The important thing to notice here is Crime rates are taken as incidents per 100,000 members of the population. Apart from the variables included there will be certain omitted variables that affect crime rates such as demographic and time effects, to cover for these omitted variables we have used Fixed and Random Effects Standard errors.

There is a possibility of Simultaneous causality bias in incarceration rate and Shall-law due to the pressure on legislatures to control Crime rates.

## INTRODUCTION

The Goal for conducting this analysis is to provide a relevant explanation about the trend of Crime rates during the period 1977 to 1999 using variables based on acceptable economic and statistical theory. Before looking at the numbers and results we got from different multiple regression models it is important to set our Economic model and theory on which we have set up our econometric model.

As per Economic theory the fundamental relationship between Crime Rates can be related to macroeconomic factors such as the condition of Economy a strongly growing economy would suggest a better job market and declining unemployment which can have an effect on crimes such as robbery but as per criminal psychology crimes such as violence and murder are driven by forces unexplained by macroeconomics such as personal conflicts, hate crimes, conflicts between two races etc. which comes under microeconomics which are harder to define.

More Strict law enforcement and more police could lead to reduction in crime as per theory a strict law against crimes is expected to create a sense of fear among crime-doers which would act as a deterrent factor and lead to crime reduction, but this theory cannot work alone as crimes like violence and murder in most cases are a result of sudden responses and individuals with different temperament.

**More Police**: This can cause a simultaneous casualty bias as the theory would suggest more policeman's will lead to a decline in crime but hiring police is an expensive strategy and so the police deployment will be more focused on areas prone to high crime rates and thus theory can fail statistically as it may seem more police leads to more crime.

**Legalizing abortion:** An Unconventional theory by Steven Levitt, Stephen J. Dubner, suggesting that law passed about legalizing abortion in 1973 could be a great explanation for the sudden crime rate drops in the US in early 1990's as the child's who would have been born and grown up to continue on path of crimes were never born, the theory may sound good but is very much in debate, one reason due to limited data and fails to explain the trend in other years.

## EXPLORATORY DATA ANALYSIS

The dataset is a balanced panel of data on 51 US states and the District of Columbia for the years 1977-1999. There is a total of 51 states x 23 years = 1173 observations.

Variables 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<br>= 0 otherwise |
| incarc_rate | the 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) |

**Vio:** Violent crime rate taken as incidents per 100,000 members of the population we expect violent crime to be highly correlated with murder rates

**Rob:** Crimes reported as robbery per 100,000 members of the population

**Mur:** Murder reported per 100,000 members of the population

**Shall:** A shall issue law is a permit to carry a concealed handgun issued by state government to any applicants who meet the following criteria: must be an adult, have no significant criminal record and no history of mental illness and successfully complete a course in firearms safety training, the above criteria in itself is issue for debate. While doing our research for the project we found many defects in the criteria itself such as there is no guarantee that a person with no criminal record will not commit a crime in future, in fact, this law can be an aid to a more serious crime as a heated argument can lead to involvement of arms. But when looking at the bigger picture we expect that right to carry concealed weapons should act as a deterrent factor in our model thus we expect the coefficient of the shall to be negative the challenge with this as an explanatory variable is that we will need to distinguish between states in our data set. There are states which have never implemented shall laws, or some states have implemented shall laws between our data period, so we will also need to consider a time fixed effect. Also, we expect a casualty bias when crime rates are higher.

**Incarc_rate:** As per our theory we expect our model to be negatively related to Crime rates, that is we expect to observe a decline in crime rates if there is an increase in the number of prisoners in the previous year. This increase will create a sense of fear and maintain law and order as the crime doers will now think before doing crimes as they are now more likely to face consequences for their crimes. We believe crimes such as robberies to be highly affected when compared with other classes of crimes. We are expecting simultaneous casualty bias with the crime rates as the policy-maker will be required to make strict laws to control for increasing rates which are also further distinguished between states.

**Density:** Our theory suggests that density is to have a varying effect on the different types of crime rates, we expect robbery rates to be highly affected than other two crimes. As per theory the states with the population having high urban settings which are likely to have high density are likely to be more correlated with crimes. Also, density is expected to have an increasing effect with densities considered as below average to have a low coefficient and even a small change in highly dense areas to be strongly correlated with an increase in crimes.

**Avginc:** Average income reflects the economic condition which is as per Economic theory negatively related to change in crime rates as a high average income will mean a strong economy preventing peoples from turning towards crime. Another theory that can be put up is to add variable explaining inequality in incomes, as per a Data study by FBI in 2016 stated that Income inequalities and crime rates are highly correlated,

**Pop**: We have a difficulty in basing a theory which can relate population of states to crime rate as the variables alone cannot be used to explain the relationship with crime but need to have an interaction with other variables such as state size, density etc. we decided to include population in our model as it is highly correlated some important variables and will be helpful in improving the estimation of those variables and omitting it can introduce endogeneity Overall we can expect population to be positively correlated with crime rates

**Pm1029:** We expect the percentage of male in state's population between age 10 to 29 to be positively correlated with crime rates to support this relationship we put the theory that its due to the demographic factor that most crimes committed involves males to prove the theory we can look for the proportion of Male prisoners to females.

**Pw1064 & Pb1064:** We expect them to be important variables in explaining the violence and murder rates in the USA during 1977 to 1999 mainly due to the demographic factors between these two races, it is evident that there have been a lot of conflicts between these two races.

## DESCRIPTIVE STATISTICS

- On average, 503 incidents of violent crime rate were reported per 100,000 members of the population from 1977 to 1999
- The average number of murder cases were 8 and robbery cases were 162 per 100,000 members of the population from 1977 to 1999
- From this, we can observe that the standard deviation for violent crime rates is very high which leads us to believe that the data points for violent crime rates are spread out over a large range of values

| Variable | Mean | Std. Dev. |
|---|---|---|
| **vio** | 503.0747 | 334.2772 |
| **mur** | 7.665132 | 7.52271 |
| **rob** | 161.8202 | 170.51 |
| **incarc_rate** | 226.5797 | 178.8881 |
| **pb1064** | 5.336217 | 4.885688 |
| **pw1064** | 62.94543 | 9.761527 |
| **pm1029** | 16.08113 | 1.732143 |
| **pop** | 4.816341 | 5.252115 |
| **avginc** | 13.7248 | 2.554543 |
| **density** | 0.3520382 | 1.355472 |

### CORRELATION MATRIX

From the correlation matrix, we observe:

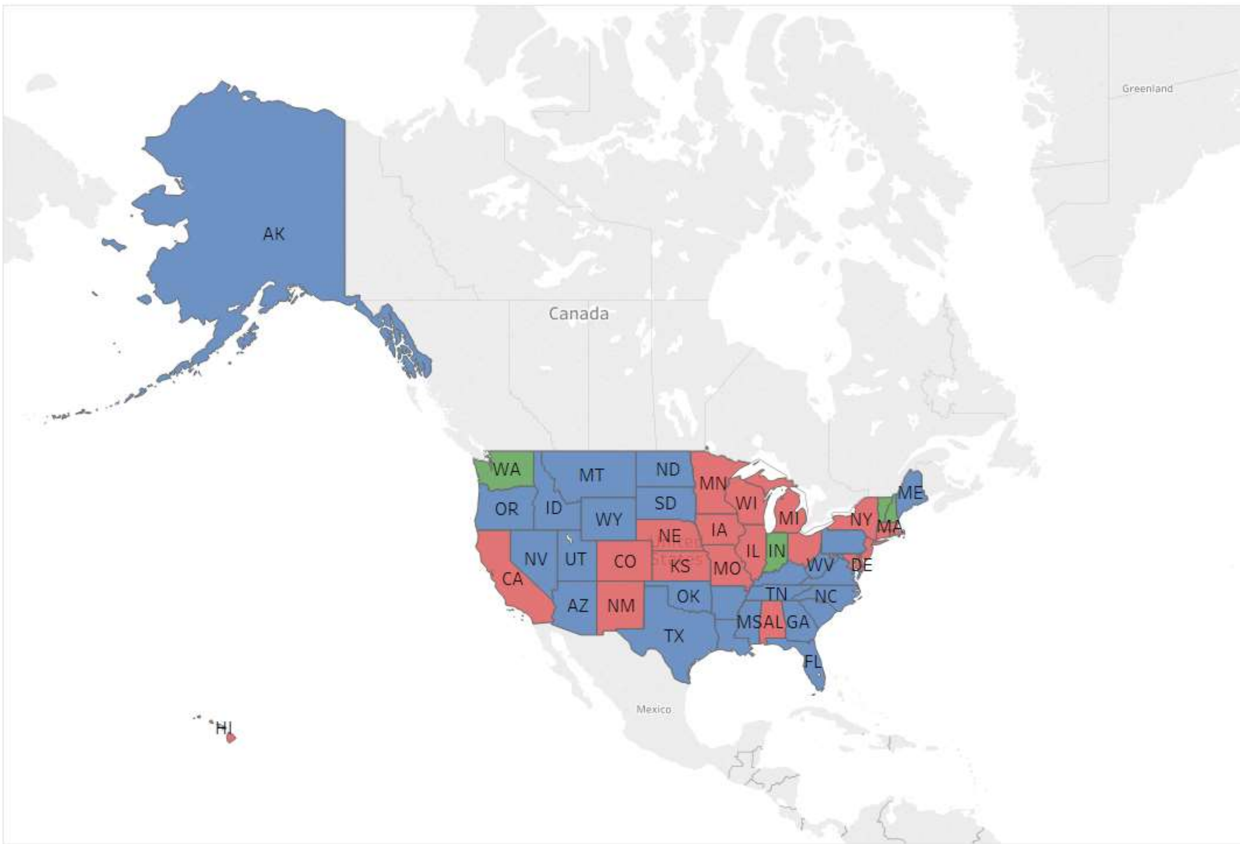
- Robbery, murder and violent crime rates are highly correlated with each other
- High density leads to higher crime rates, especially robbery activities

```
. corr incarc_rate rob mur vio density avginc pop pm1029 pw1064 pb1064 shall
(obs=1,173)

             | incarc~e      rob      mur      vio  density   avginc      pop   pm1029   pw1064   pb1064    shall
-------------+---------------------------------------------------------------------------------------------------
 incarc_rate |   1.0000
         rob |   0.5668   1.0000
         mur |   0.7096   0.7976   1.0000
         vio |   0.7027   0.9071   0.8265   1.0000
     density |   0.5593   0.7818   0.7486   0.6647   1.0000
      avginc |   0.4615   0.4148   0.2206   0.4080   0.3433   1.0000
         pop |   0.0953   0.3172   0.0999   0.3190  -0.0780   0.2152   1.0000
      pm1029 |  -0.4463  -0.0860   0.0150  -0.1696  -0.0637  -0.5279  -0.0975   1.0000
      pw1064 |  -0.5271  -0.5842  -0.6154  -0.5730  -0.5551  -0.1912  -0.0654  -0.0126   1.0000
      pb1064 |   0.5308   0.5812   0.6018   0.5698   0.5432   0.2627   0.0581   0.0162  -0.9820   1.0000
       shall |   0.0424  -0.2125  -0.1794  -0.2069  -0.1126  -0.0000  -0.1244  -0.2772   0.2123  -0.1839   1.0000
```

## EXPLORATORY DATA ANALYSIS

The graph divides the United States on the basis of their shall law implementation policy. This gives us an overview of the variation in shall law policy in the country

Shall Law Grouped States



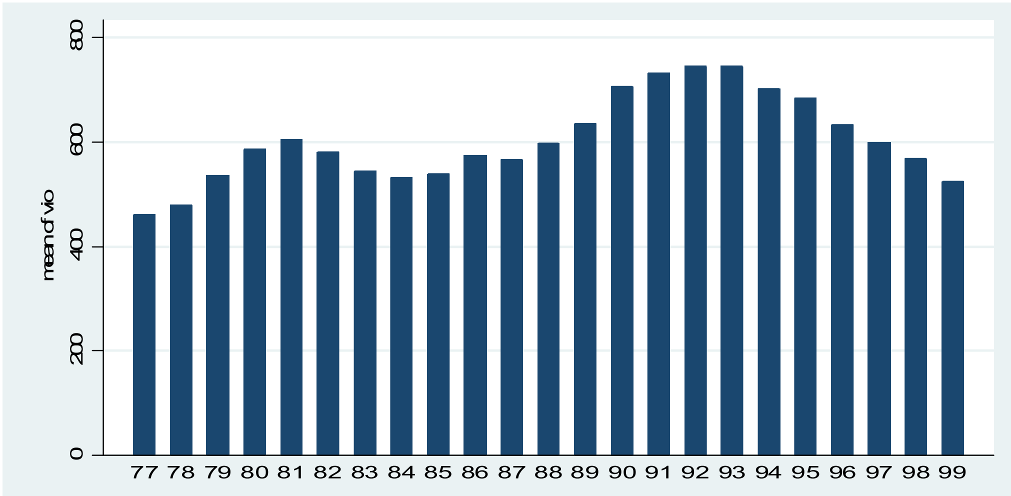

Map based on Longitude (generated) and Latitude (generated). Color shows details about stateid. The marks are labeled by State Code. Details are shown for State.

stateid
- Shall Law Implemented between 1977-1999
- Shall Law since 1977
- Shall Law Not Implemented till 1999

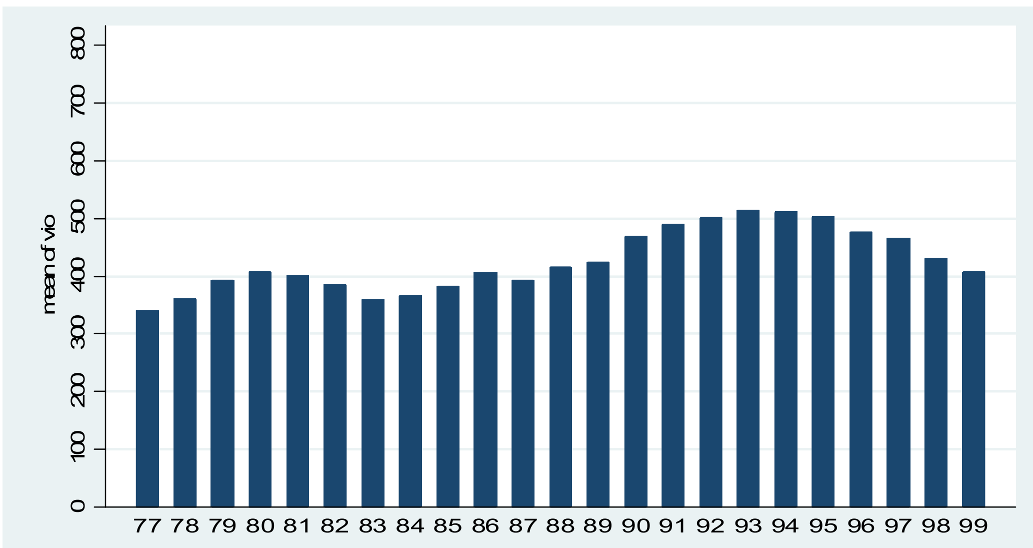
From the data, we got the following insights:

- 4 out of 51 states had shall law applicable from the beginning i.e. from 1977 to 1999
- 25 states implemented shall law in between the period of 1977 to 1999
- 22 out of 51 states in the data, never had shall law implemented in the given period

In our further analysis, we divided the data on the basis of shall law implementation, then compared and observed the trend in these specific groups.




*Graph 1: The above graph is the mean of violent crime rates in states with no shall law*




*Graph 2: The above graph is the mean violent crime rate from states that had shall law at some point from the years 1977 to 1999*

From these graphs we can make the following observations:

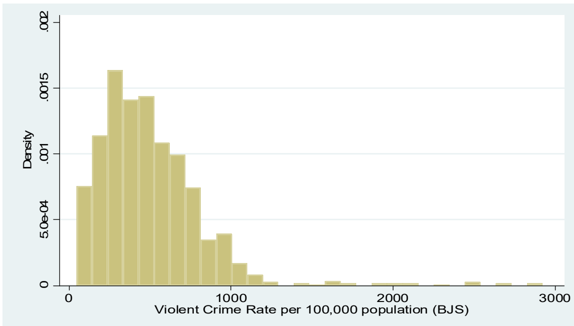
- The trend of average crime rate is similar in states with or without shall law
- The increase and decrease in violent crime rate look similar
- The crime rate sees an increase from the year 1990 to 1993 for both the groups. This makes us believe that there was a rise in violent criminal activities across the US states in these years irrespective of the shall law implementation

We generated the following variables:

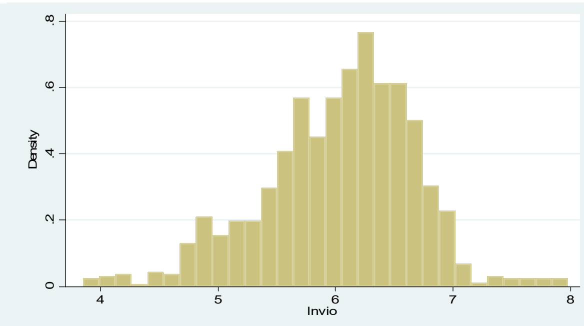
- lnvio = ln(vio)
- lnmur = ln(mur)
- lnrob= ln(rob)

- lnincarc_rate = ln(incarc_rate)

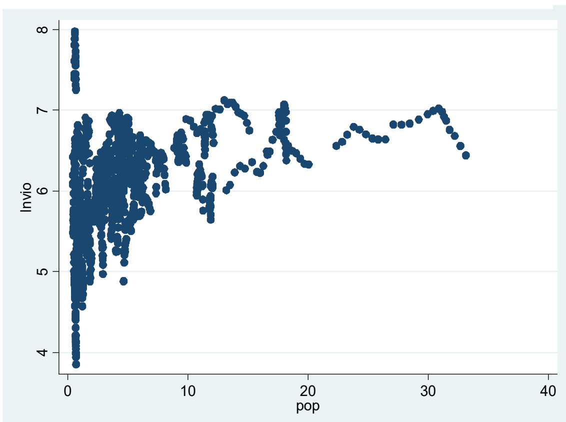
The logarithmic form of these variables has lesser skewness in their distribution and also easier for interpretation. Hence from now onward, we have used these variables for our analysis




*Graph 3: Vio frequency density histogram*

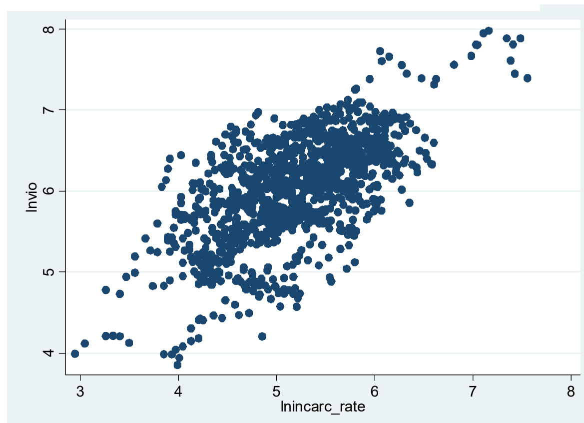



*Graph 4: lnvio frequency density histogram*




*Graph 5: lnvio versus population*

*We observe a positive relationship between population and violent crimes rates for higher values of the population.*




*Graph 6: lnvio versus incarc_rate*

*We clearly see a positive trend here. As incarceration rate increases, violent crime rate also increases*

From Graph6, we observe a positive relationship between incarceration rate and violent crime rates, which means that as the average sentencing of prisoners increases, there is a rise in violent crime rates This does not seem to be coherent with real-life expectations. In reality, as the incarceration rate increases, the violent crime rates should ideally decrease. We sense a problem of simultaneous causality, which leads to the biases in results.

## REGRESSION MODELLING AND HYPOTHESIS TESTING

### LINEAR REGRESSIONS

#### LNVIO DEPENDENT VARIABLE

**Model 1: lnvio= $\beta_0 + \beta_1$shall**

| Source | SS | df | MS | | | |
|---|---|---|---|---|---|---|
| | | | | Number of obs | = | 1,173 |
| | | | | F(1, 1171) | = | 111.08 |
| Model | 42.3348289 | 1 | 42.3348289 | Prob > F | = | 0.0000 |
| Residual | 446.29673 | 1,171 | .381124449 | R-squared | = | 0.0866 |
| | | | | Adj R-squared | = | 0.0859 |
| Total | 488.631558 | 1,172 | .416921125 | Root MSE | = | .61735 |

| lnvio | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| shall | -.4429646 | .0420294 | -10.54 | 0.000 | -.525426 | -.3605032 |
| _cons | 6.134919 | .020717 | 296.13 | 0.000 | 6.094272 | 6.175566 |

In the above model, we see that implementation of shall law has a huge impact on violent criminal activities. If a state has a shall law, the violent crime rates decrease by 44% which is a huge decrease

The coefficient of shall law is highly significant in the above linear regression

**Model 2: lnvio= $\beta_0 + \beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc**

```
. reg vio_log shall  incarc_rate  density pop avginc
```

| Source | SS | df | MS | | | |
|---|---|---|---|---|---|---|
| | | | | Number of obs | = | 1,173 |
| | | | | F(5, 1167) | = | 274.31 |
| Model | 264.002521 | 5 | 52.8005043 | Prob > F | = | 0.0000 |
| Residual | 224.629037 | 1,167 | .192484179 | R-squared | = | 0.5403 |
| | | | | Adj R-squared | = | 0.5383 |
| Total | 488.631558 | 1,172 | .416921125 | Root MSE | = | .43873 |

| vio_log | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| shall | -.3935666 | .0307183 | -12.81 | 0.000 | -.4538358 | -.3332973 |
| incarc_rate | .0017224 | .0000933 | 18.45 | 0.000 | .0015393 | .0019055 |
| density | .0450569 | .0119086 | 3.78 | 0.000 | .0216922 | .0684215 |
| pop | .0419058 | .0025775 | 16.26 | 0.000 | .0368487 | .0469629 |
| avginc | .0093228 | .0058345 | 1.60 | 0.110 | -.0021245 | .0207701 |
| _cons | 5.387007 | .0741543 | 72.65 | 0.000 | 5.241517 | 5.532498 |

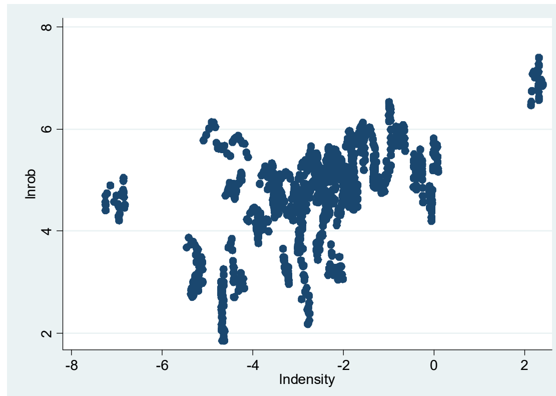
As we include demographic factors like population average income and density, we see that the effect of shall law reduces to 39% as compared to 44%. Hence, adding more control variables the effect of shall law drops as the effect of these omitted variables was picked up by shall law making it bias. Except for average income all the other variables are significant.

## LNROB DEPENDANT VARIALBE

We consider that density will have an increasing effect on robbery rates, so we did a log-log regression of density and robbery rate. Marginal effect of Density will be lower for low density states and higher for states with higher density is expected on robberies.

**Model 2: lnrob= $\beta_0 + \beta_1$lndensity**

```
. reg lnrob lndensity

      Source |       SS           df       MS      Number of obs   =     1,173
-------------+----------------------------------   F(1, 1171)      =    645.04
       Model |  379.353319         1  379.353319   Prob > F        =    0.0000
    Residual |  688.679804     1,171  .588112557   R-squared       =    0.3552
-------------+----------------------------------   Adj R-squared   =    0.3546
       Total |  1068.03312     1,172   .91129106   Root MSE        =    .76688

------------------------------------------------------------------------------
       lnrob |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lndensity |   .3620704   .0142561    25.40   0.000        .3341    .3900408
       _cons |   5.607264   .0426563   131.45   0.000     5.523573    5.690956
------------------------------------------------------------------------------
```




The above regression and graph confirm that here is positive elasticity in density and robbery rate. 1% increase in density rate increases robbery rate by 0.36%

## POOLED OLS ESTIMATION

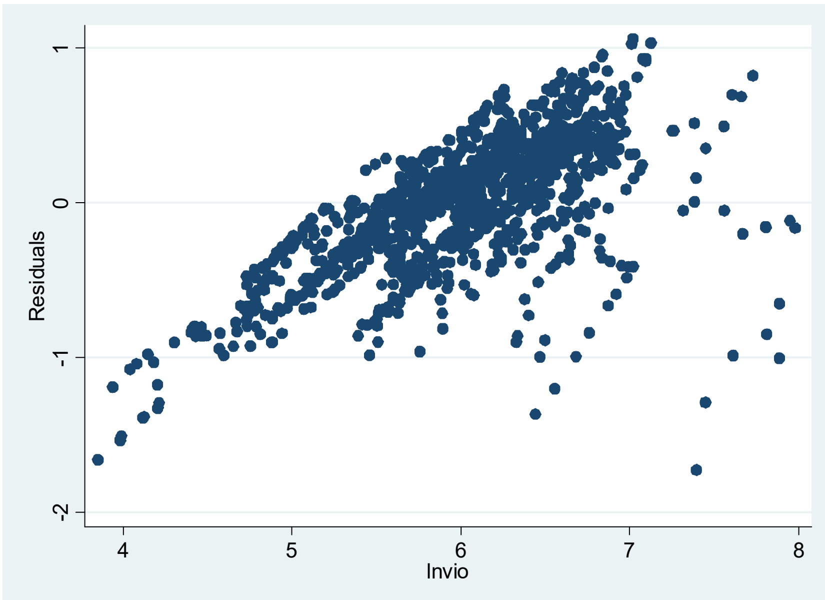
**Model 4: lnvio= $\beta_0 + \beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc + $\beta_5$pb1064 + $\beta_6$pw1064 + $\beta_7$ pm1029**

```
. reg lnvio shall incarc_rate density pop avginc pb1064 pw1064 pm1029

      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

------------------------------------------------------------------------------
       lnvio |      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
         pop |   .0427098   .0025588    16.69   0.000     .0376894    .0477303
      avginc |   .0012051   .0077802     0.15   0.877    -.0140597      .01647
      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
       _cons |   2.981738   .5433938     5.49   0.000     1.915598    4.047879
------------------------------------------------------------------------------
```

## CHECK FOR HETEROSKEDASTICITY

Scatter plot of residuals versus the violent crime rates

From the graph, we see that there is evidence of heteroscedasticity, as the variation in the dataset increases for larger values. We can reconfirm our evidence by statistical tests.




```
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 |

**Null Hypothesis**: There is homoscedasticity

**Alternate Hypothesis**: There is evidence for heteroscedasticity

From the White test, we find strong evidence for heteroscedasticity in the above model and hence we ran the pooled OLS model with white robust errors and cluster-robust standard errors.

**Model 5: lnvio= $\beta_0$ + $\beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc + $\beta_5$pb1064 + $\beta_6$pw1064 + $\beta_7$ pm1029, with white robust standard errors**

```
. reg lnvio shall incarc_rate density pop avginc pb1064 pw1064 pm1029, robust
```

Linear regression

| | | |
|---|---|---|
| Number of obs | = | 1,173 |
| F(8, 1164) | = | 95.67 |
| Prob > F | = | 0.0000 |
| R-squared | = | 0.5643 |
| Root MSE | = | .42769 |

| lnvio | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| shall | -.3683869 | .0347879 | -10.59 | 0.000 | -.436641 | -.3001329 |
| incarc_rate | .0016126 | .0001807 | 8.92 | 0.000 | .0012581 | .0019672 |
| density | .0266885 | .0143494 | 1.86 | 0.063 | -.0014651 | .054842 |
| pop | .0427098 | .0031466 | 13.57 | 0.000 | .0365361 | .0488836 |
| avginc | .0012051 | .0072778 | 0.17 | 0.869 | -.013074 | .0154842 |
| pb1064 | .0808526 | .0199924 | 4.04 | 0.000 | .0416274 | .1200778 |
| pw1064 | .0312005 | .0097271 | 3.21 | 0.001 | .012116 | .0502851 |
| pm1029 | .0088709 | .0120604 | 0.74 | 0.462 | -.0147917 | .0325334 |
| _cons | 2.981738 | .6090198 | 4.90 | 0.000 | 1.786839 | 4.176638 |

Observations from the Pooled OLS model:

- Shall law implementation can reduce the violent crime rate by 36%
- High incarceration rate leads to increase  in violent activities
- Density is not significant at 5% confidence interval
- Higher population leads to higher violent crimes at 4% coefficient estimate
- Black population states have 8% higher crime rates

**Model 6: lnvio= $\beta_0$ + $\beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc + $\beta_5$pb1064 + $\beta_6$pw1064 + $\beta_7$ pm1029, with clustered robust standard errors**

```
. reg vio_log shall incarc_rate pb1064 pw1064 pm1029 pop avginc density, 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)

| vio_log | 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 |
| 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 |
| pop | .0427098 | .011729 | 3.64 | 0.001 | .0191515 | .0662681 |
| avginc | .0012051 | .0240808 | 0.05 | 0.960 | -.0471626 | .0495728 |
| density | .0266885 | .0414909 | 0.64 | 0.523 | -.0566485 | .1100255 |
| _cons | 2.981738 | 2.166513 | 1.38 | 0.175 | -1.369831 | 7.333307 |

We see that the clustered robust standard errors are significantly higher than OLS standard errors for homoscedasticity and the white errors. Clustered standard errors adjust for the panel nature of the data, serial correlation between errors and heteroscedasticity.

The Pooled OLS model does not consider the panel nature of the dataset and considers all observations independent of each other. Thus, the results from pooled OLS cannot be considered close to reality as in reality, there is a correlation between same entities in different time periods.

Hence, we consider Fixed Effects estimation which will give relevant results for this dataset controlling for unobserved heterogeneity and the panel nature.

## FIXED EFFECTS ESTIMATION

**Model 7: lnvio= $\beta_0 + \beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc + $\beta_5$pb1064 + $\beta_6$pw1064 + $\beta_7$ pm1029, fixed effects with clustered robust standard errors**

```
. xtreg lnvio shall incarc_rate density pop avginc pb1064 pw1064 pm1029, fe 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)
------------------------------------------------------------------------------
             |               Robust
       lnvio |      Coef.   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
         pop |   .0115247    .014224     0.81   0.422    -.0170452    .0400945
      avginc |  -.0092037   .0129649    -0.71   0.481    -.0352445     .016837
      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
       _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)
------------------------------------------------------------------------------
```

- The results are very different when we observe the estimation using fixed effects
- The shall law coefficient drops from 36.8% to 4.6% which is a large reduction and a true reflection of the reality
- This also strengthens our intuition that there was unobserved heterogeneity in the data
- Also, the significance of shall law in no longer relevant at 5% confidence interval
- Thus, Entity Fixed Effects is a better measure of shall law implementation in US states

## ENTITY AND TIME FIXED EFFECTS ESTIMATION

Entity Fixed effects consider the variation only within entities and not across the entities. There is a possibility that an omitted variable varies over time but not across entities. Entity FE considers only the time-invariant effects hence adding the dummy time variables will be useful for our interpretation.

There are states which implemented shall law somewhere in between 1977 to 1999, this effect can be captured by time fixed effect estimation.

We create N-1 dummy time variables and then use OLS estimation to make our interpretations

**Model 8:** $Y_{it} = \beta_0 + \beta_1 X_{it} + \delta_2 year2_{it} + \ldots \delta_T yearT_{it} + u_{it}$

```
. xtreg vio_log shall incarc_rate pb1064 pw1064 pm1029 pop avginc density i.year, 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  = 0.4180                                         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)
```

| vio_log | Coef. | Robust 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 |
| 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 |
| pop | -.0047544 | .0152294 | -0.31 | 0.756 | -.0353436 | .0258347 |
| avginc | .0009587 | .0164931 | 0.06 | 0.954 | -.0321688 | .0340861 |
| density | -.091555 | .1238622 | -0.74 | 0.463 | -.3403396 | .1572296 |
| 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) | | | | |

From this model we see that the effect of shall law has further fallen down to just 2.8% and it is also far from zero.

To confirm which model to use Entity FE versus Time and Entity FE, we perform a joint hypothesis testing.

**Null hypothesis:** The dummy time variables are all zero

**Alternate Hypothesis**: At least one of the dummy time variables is non zero

```
. 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
```

From the above joint hypothesis testing, we reject null hypothesis as p-value is almost 0 and F-statistic is as high as 21.62

Hence, we confirm that the time effects are jointly statistically significant and **Time and Entity Fixed effects** explains our dataset the best.

## RANDOM EFFECTS ESTIMATION

**Model 9: lnvio= $\beta_0$ + $\beta_1$shall + $\beta_2$incarc_rate + $\beta_2$density + $\beta_3$pop + $\beta_4$avginc + $\beta_5$pb1064 + $\beta_6$pw1064 + $\beta_7$ pm1029, random effects**

The Random effects estimator though seems significant will be less relevant in this scenario.

Random effects are more sensible when the entities are randomly drawn from a population. But in this case, the entities are fixed i.e. 50 states of the US and the state of Columbia.

Though RE estimator will be more efficient, this data set will be explained better using FE estimator.

This can be confirmed using the Hausman Test to compare the coefficient estimates from the random-effects model to those from the fixed effects model

```
. xtreg vio_log shall incarc_rate pb1064 pw1064 pm1029 pop avginc density,re

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)      =     337.19
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

| vio_log | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| shall | -.069609 | .0190835 | -3.65 | 0.000 | -.107012 | -.032206 |
| incarc_rate | .0001888 | .0000687 | 2.75 | 0.006 | .0000541 | .0003235 |
| pb1064 | .1067022 | .0132976 | 8.02 | 0.000 | .0806394 | .1327649 |
| pw1064 | .0400716 | .0050987 | 7.86 | 0.000 | .0300783 | .050065 |
| pm1029 | -.0375292 | .0060462 | -6.21 | 0.000 | -.0493794 | -.0256789 |
| pop | .0225755 | .0063498 | 3.56 | 0.000 | .0101301 | .035021 |
| avginc | -.0105112 | .0058749 | -1.79 | 0.074 | -.0220258 | .0010034 |
| density | .0661588 | .037363 | 1.77 | 0.077 | -.0070713 | .1393889 |
| _cons | 3.525463 | .3874011 | 9.10 | 0.000 | 2.766171 | 4.284755 |
| sigma_u | .33790775 | | | | | |
| sigma_e | .16072287 | | | | | |
| rho | .81550462 | (fraction of variance due to u_i) | | | | |

```
. estimates store Random
```

## HAUSMAN TEST FOR RANDOM VERSUS FIXED EFFECTS ESTIMATOR

**Null Hypothesis**: No endogeneity present $\mathbf{B_{FE}} \rightarrow \beta$ , $\mathbf{B_{RE}} \rightarrow \beta$

**Alternate Hypothesis**: Endogeneity exists $\mathbf{B_{FE}} \rightarrow \beta$ , $\mathbf{B_{RE}} \rightarrow C \neq \beta$

From the Hausman test, we have used we can see that chi-square value is 31.86 and the p-value is less than 1%.

**Thus, we reject the null hypothesis of no endogeneity and conclude that we should use the fixed effect model.**

**Note:** For Hausman Test we are using the standard errors as the test will not work for robust errors.

```
. hausman Fixed Random
```

| | Coefficients (b) Fixed | (B) Random | (b-B) Difference | sqrt(diag(V_b-V_B)) S.E. |
|---|---|---|---|---|
| shall | -.0461415 | -.069609 | .0234675 | . |
| incarc_rate | -.000071 | .0001888 | -.0002598 | .0000635 |
| pb1064 | .1042804 | .1067022 | -.0024217 | .011767 |
| pw1064 | .0408611 | .0400716 | .0007895 | . |
| pm1029 | -.0502725 | -.0375292 | -.0127434 | .0021099 |
| pop | .0115247 | .0225755 | -.0110508 | .0059821 |
| avginc | -.0092037 | -.0105112 | .0013075 | .0006269 |
| density | -.1722901 | .0661588 | -.2384489 | .0763882 |

```
                           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)
```

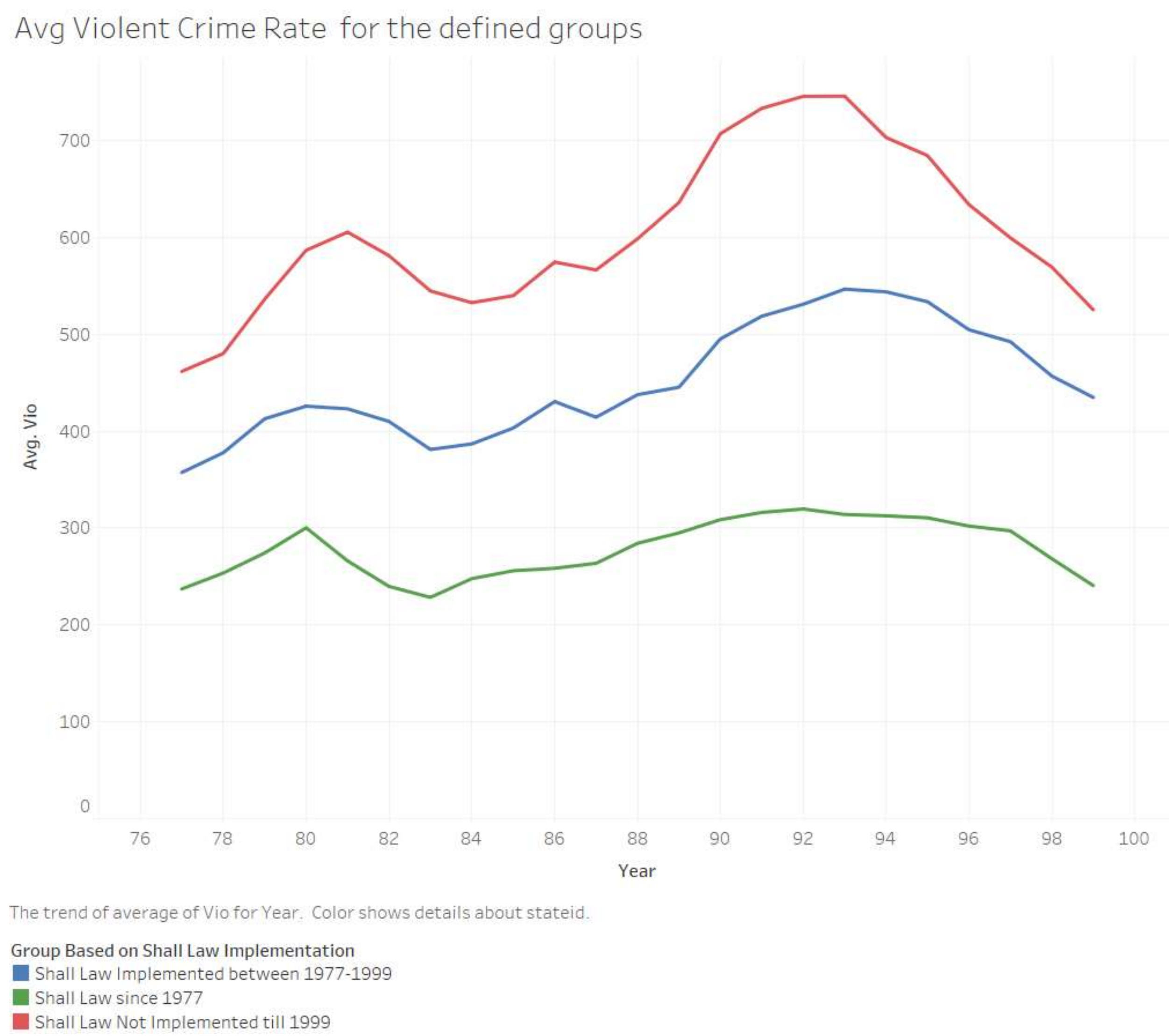
## CONCLUSION AND RECOMMENDATIONS

From the above regression modeling and hypothesis testing, we conclude that:

- Entity and Time Fixed Effects model explains best the effect of shall law and incarceration rate on violent crime activities

| SHALL LAW EFFECT | lnvio | lnrob | lnmur |
|---|---|---|---|
| **Shall law coefficient** | -0.027 | 0.026 | -0.015 |
| **Shall law significance** | 0.495 | 0.61 | 0.697 |

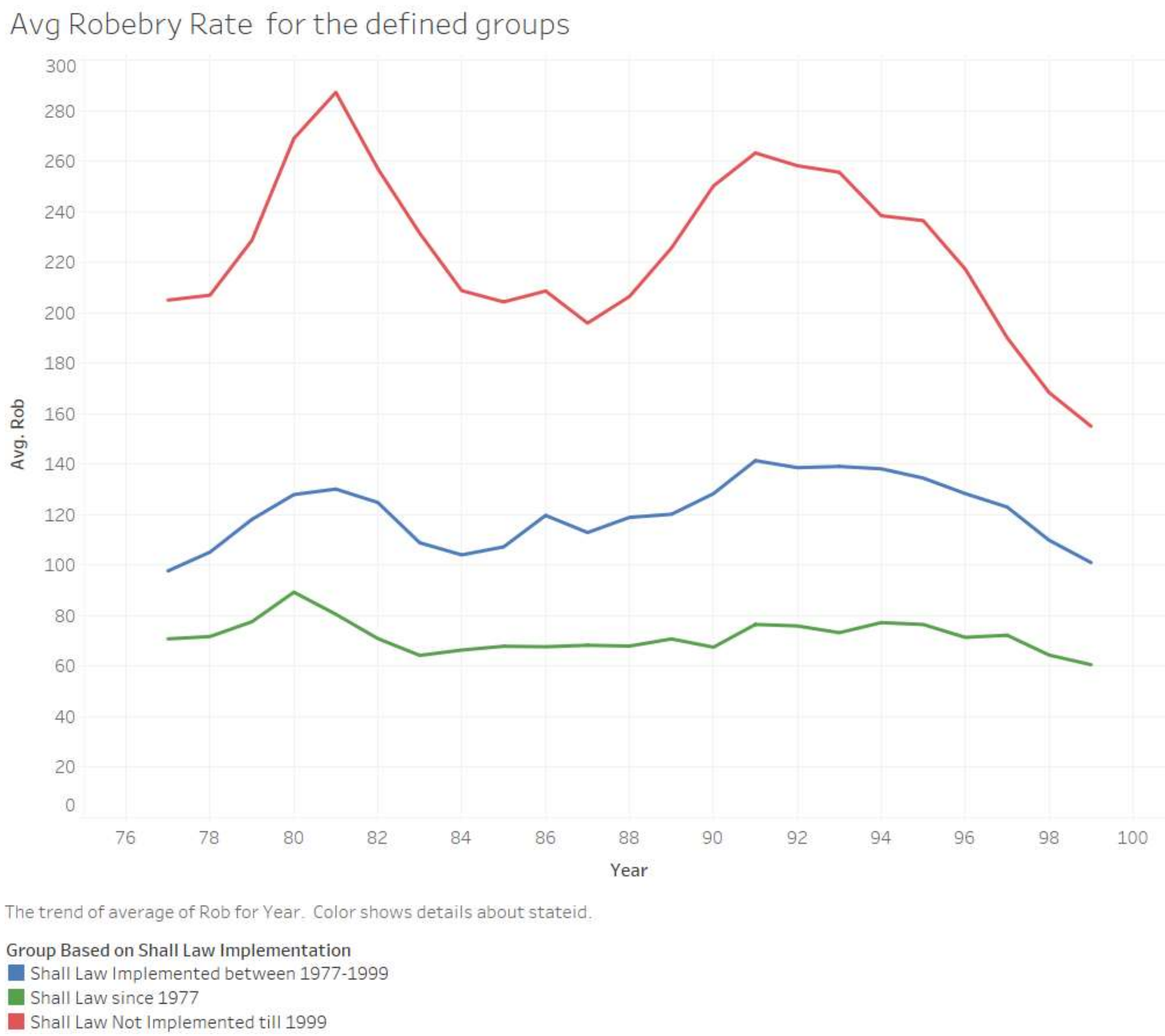
- From the above results, we can say that there is no significant effect of shall law implementation on violent crime rates, robbery or murder activities.



The above graph shows the average violent crime rate for different groups depending on the year the implemented shall law.

From the above graph we make following conclusions:

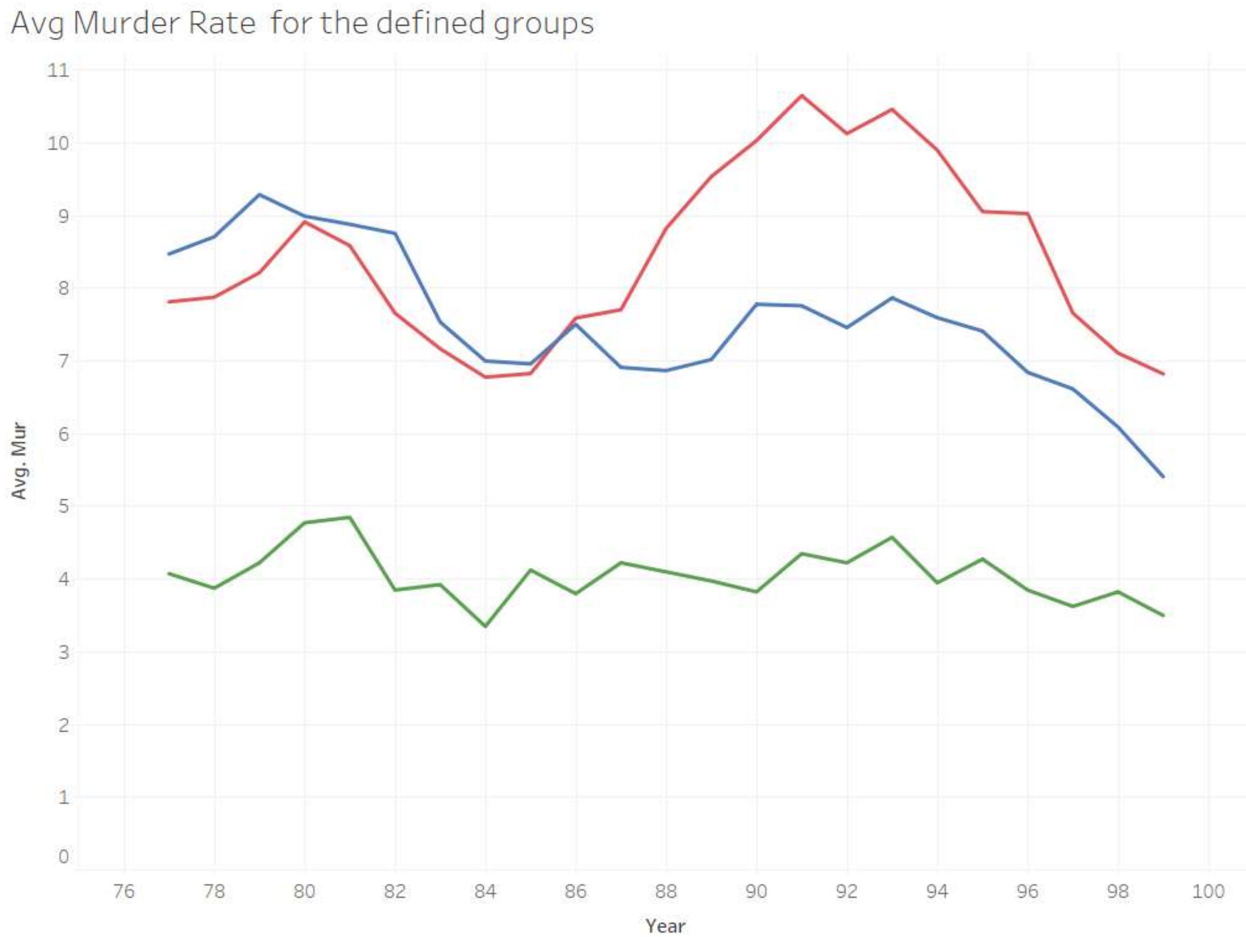
- It is evident that irrespective of shall law implementation, there are significant drops in crime rates for all states.
- The states that had shall law also saw an increase in crime rate activities in the years 1990-1993
- Thus shall law fails to explain the effect of crime rate in the United States and the results are also not statistically significant from the regression models




The above graph shows the average robbery rate for different groups depending on the year the states implemented shall law.

Observations from the graph:

- This graph also reinstates our inference that shall law does not explain the robbery rates in the United States as the robbery rate for shall law implemented states shows no reduction over time
- The spike in graph during late 1970's and early eighties can be related to the global economic recession




The trend of average of Mur for Year. Color shows details about stateid.

**Group Based on Shall Law Implementation**
- Shall Law Implemented between 1977-1999
- Shall Law since 1977
- Shall Law Not Implemented till 1999

The above graph shows the average murder rate for different groups depending on the year the states implemented shall law.

Observations from the graph:

- States which had shall law from beginning has failed to witness a reduction in murders
- States which never applied shall law witnessed a sudden drop in murders just like violent and robberies rates
- The states which applied shall law in between our data period showed a drop-in murder rate

| Incarc_rate EFFECT | lnvio | lnrob | lnmur |
|---|---|---|---|
| **Incarc_rate coefficient** | .000076 | .0000314 | -.0001164 |
| **Incarc_rate significance** | 0.71 | 0.92 | 0.75 |

The incarceration rate is expected to have a moderately negative effect on the above activities and is subject to diminishing effects.

But from the above results, we observe that it is highly insignificant for all the three variables: lnvio, lnmur, and lnrob and the coefficient estimates are also almost negligible. This may be due to casualty bias.

Thus, we cannot rely on estimates of our model to study effects of incarceration rate on violent crime rates, robbery, and murders.

## LIMITATIONS OF MODELS

### SIMULTANEOUS CASUALTY BIAS

**Crime rate = $\beta_0 + \beta_1$Shall Law+ $\beta_2$incarceration rate + e**

In the above equation, the crime rate is affected by variation in incarceration rate, but on the other hand, incarceration rate is also affected by crime rates. This introduces the problem of simultaneous causality bias which makes our model inconsistent and biased.

We also consider that shall law has a simultaneous bias on crime rates. As the cultural attitude and political influence towards guns and crimes in states could be the reason that the government implemented shall law in the state

### OMITTED VARIABLE BIAS

There are various other factors that can affect crime rates in the states other than demographic and shall law policy.

These factors as not considered, will be unobserved in nature and cause unobserved heterogeneity making our model inconsistent and biased. Some of these variables could be:

- Economic condition
- Quality of police
- Other crime-prevention programs
- The elected political party in the state
- Public safety budget of different states
- Abortion rates in different states
- Drugs consumption in a state

These omitted variables cause the problem of endogeneity and lead to failure of our models.

This problem of Endogeneity can be solved by considering Instrumental Variables which can found by considering some exogenous source of variation in shall law and incarceration rate arising from a random phenomenon.