

# Do more guns lead to less crime?

Applied Econometrics & Time-Series Analysis Project Report  
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## INTRODUCTION

The impact of guns on crime in America has triggered a lot of public debate.

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

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

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

#### Variable Definitions :-

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

With the provide information we need to carry a study whether providing guns to the citizens who are eligible for the mentioned criteria will reduce the crime rate .

In the provide information we have three different crime rate :- **Violence, Robbery and Murder** , But our study mainly focus on **Violent crime rate** but **we will extend out study to see how Robbery, Murder and Other Violence(vio-(rob+mur))** are controlled using shall law and with other explanatory variables and we can see whether all 4 crime rates are travelling in same direction or in different direction .

## EXPLORATORY DATA ANALYSIS

We are working on a balanced panel dataset on 50 US states, plus the District of Columbia over a 23-year period of time. The total number of observations is 1173 and there's no null values in the dataset.

Before building our hypotheses and models, we will do descriptive analysis and some exploratory analysis to have an overview, as well as better insights about our data such as relationship between variables, trend, ... Besides 3 dependent variables (vio, rob, mur), we will also focus on 2 important explanatory variables - shall and incarc\_rate to answer our main the question "Do more guns reduce crime?"

## 1. Descriptive statistics:

Variable	Vio	Rob	Mur	Other Vio	incarc_rate
Mean	503.0747	161.8202	7.665132	333.5893	226.5797
Std Deviation	334.2772	170.51	7.52271	188.0383	178.8881
Variance	111741.2	29073.65	56.59116	35358.41	32000.95
Skewness	2.538371	3.882311	5.785826	1.54	3.881709
Min	47	6.4	0.2	39.6	19
Max	2921.8	1635.1	80.6	1613.7	1913
Count	1173	1173	1173	1173	1173

Variable	pb1064	pw1064	pm1029	avginc	density	pop	Shall
Mean	5.336217	62.94543	16.08113	13.7248	0.3520382	4.816341	0.2429668
Std Deviation	4.885688	9.761527	1.732143	2.554543	1.355472	5.252115	0.4290581
Variance	23.86994	95.28741	3.000321	6.525687	1.837304	27.58471	0.1840908
Skewness	2.351575	2.223298	0.2675794	0.7342556	6.694125	2.430632	1.198639
Min	0.2482066	21.78043	12.21368	8.554884	0.0007071	0.402753	0
Max	26.97957	76.52575	22.35269	23.64671	11.10212	33.14512	1
Count	1173	1173	1173	1173	1173	1173	1173

From Statistics we can observe that Variance for Vio, rob, othervio, Incarc\_rate are higher compared to other variables

Also, Vio, Rob, Mur, Othervoi, Incarc\_rate, density data have a significant skewness and might need transformation only we can decide after looking to distribution and box plots of the same .

## 2. Correlation between variables:

	year	vio	mur	rob	incarc_rate	pb1064	pw1064
year	1.0000						
vio	0.1214	1.0000					
mur	-0.0330	0.8265	1.0000				
rob	-0.0142	0.9071	0.7976	1.0000			
incarc_rate	0.5041	0.7027	0.7096	0.5668	1.0000		
pb1064	0.0686	0.5698	0.6018	0.5812	0.5308	1.0000	
pw1064	-0.0335	-0.5730	-0.6154	-0.5842	-0.5271	-0.9820	1.0000
pm1029	-0.8658	-0.1696	0.0150	-0.0860	-0.4463	0.0162	-0.0126
pop	0.0594	0.3190	0.0999	0.3172	0.0953	0.0581	-0.0654
avginc	0.5252	0.4080	0.2206	0.4148	0.4615	0.2627	-0.1912
density	-0.0040	0.6647	0.7486	0.7818	0.5593	0.5432	-0.5551
stateid	-0.0000	-0.3170	-0.2428	-0.2507	-0.2171	-0.3105	0.3112
shall	0.3794	-0.2069	-0.1794	-0.2125	0.0424	-0.1839	0.2123
othervio	0.2301	0.9221	0.7060	0.6738	0.7067	0.4618	-0.4643
	pm1029	pop	avginc	density	stateid	shall	othervio
pm1029	1.0000						
pop	-0.0975	1.0000					
avginc	-0.5279	0.2152	1.0000				
density	-0.0637	-0.0780	0.3433	1.0000			
stateid	0.0084	-0.0637	-0.2035	-0.1640	1.0000		
shall	-0.2772	-0.1244	-0.0000	-0.1126	0.1873	1.0000	
othervio	-0.2242	0.2754	0.3403	0.4428	-0.3266	-0.1679	1.0000

From the above output we can observe that

Vio is highly correlated with mur, rob, othervio, incarceration\_rate which is understandable w.r.t mur and rob but vio increases with incarceration\_rate is not a good sign to our study may be some causality bias is expected let's see .

Vio is moderately correlated with pb1064, pw1064, avginc , and density which is quite fine for now .

Vio is least correlated with shall, pop , This may not be accurate as the number of shall carry law record is much lower than no shall-carry law in this dataset .

There's also a positive correlation between density and crime rate, which makes sense to us.

The percentage of white in the population is strongly negatively correlated with the percentage of black in the population. And, as time goes by, the percentage of young male in the population decrease.

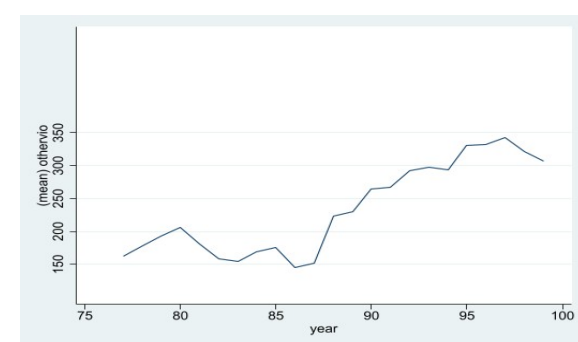
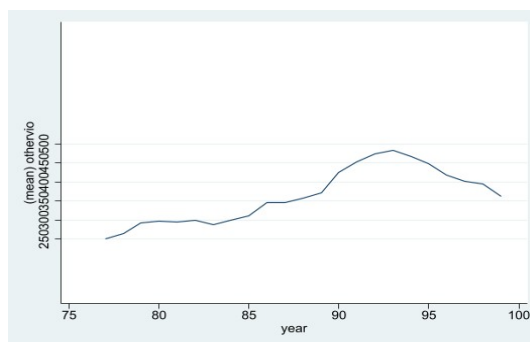
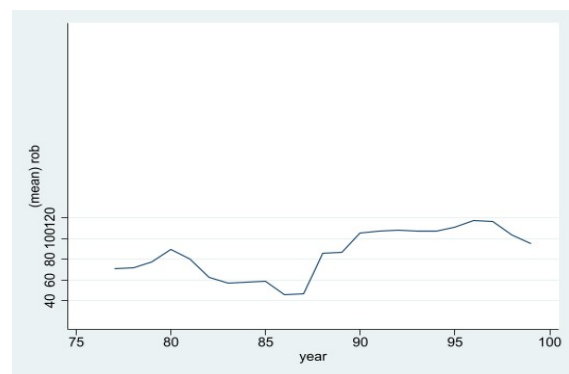
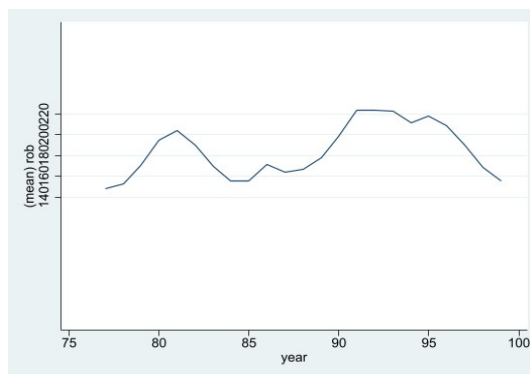
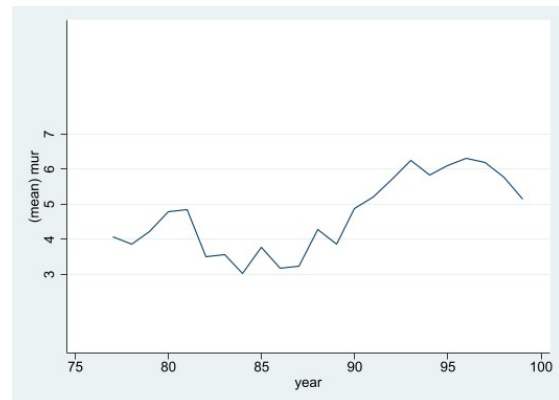
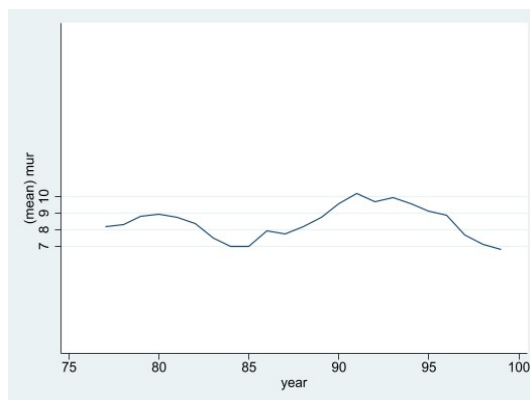
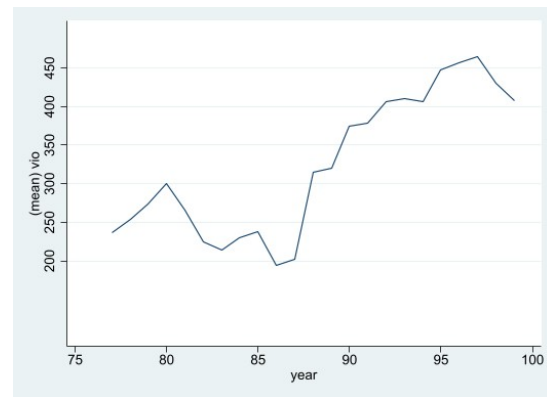
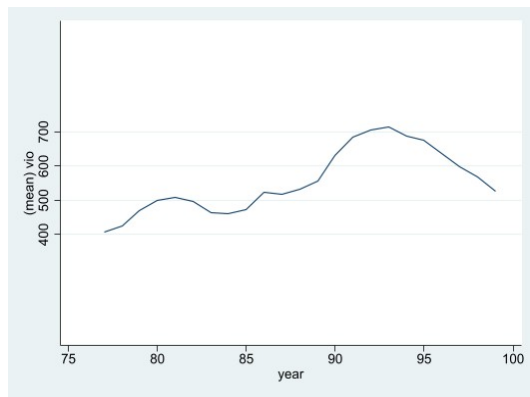
### 3. Variables studying in detail

#### 3.1 Crimes across years

Let's try to plot the different types of crimes varied across years with and without shall law

Without Shall Law

Shall Law



From the above plots we can observe that crime rates are coming down when shall law is in place compared with no shall law in place

We can observe that on average vio rate is decreased by 3-4%

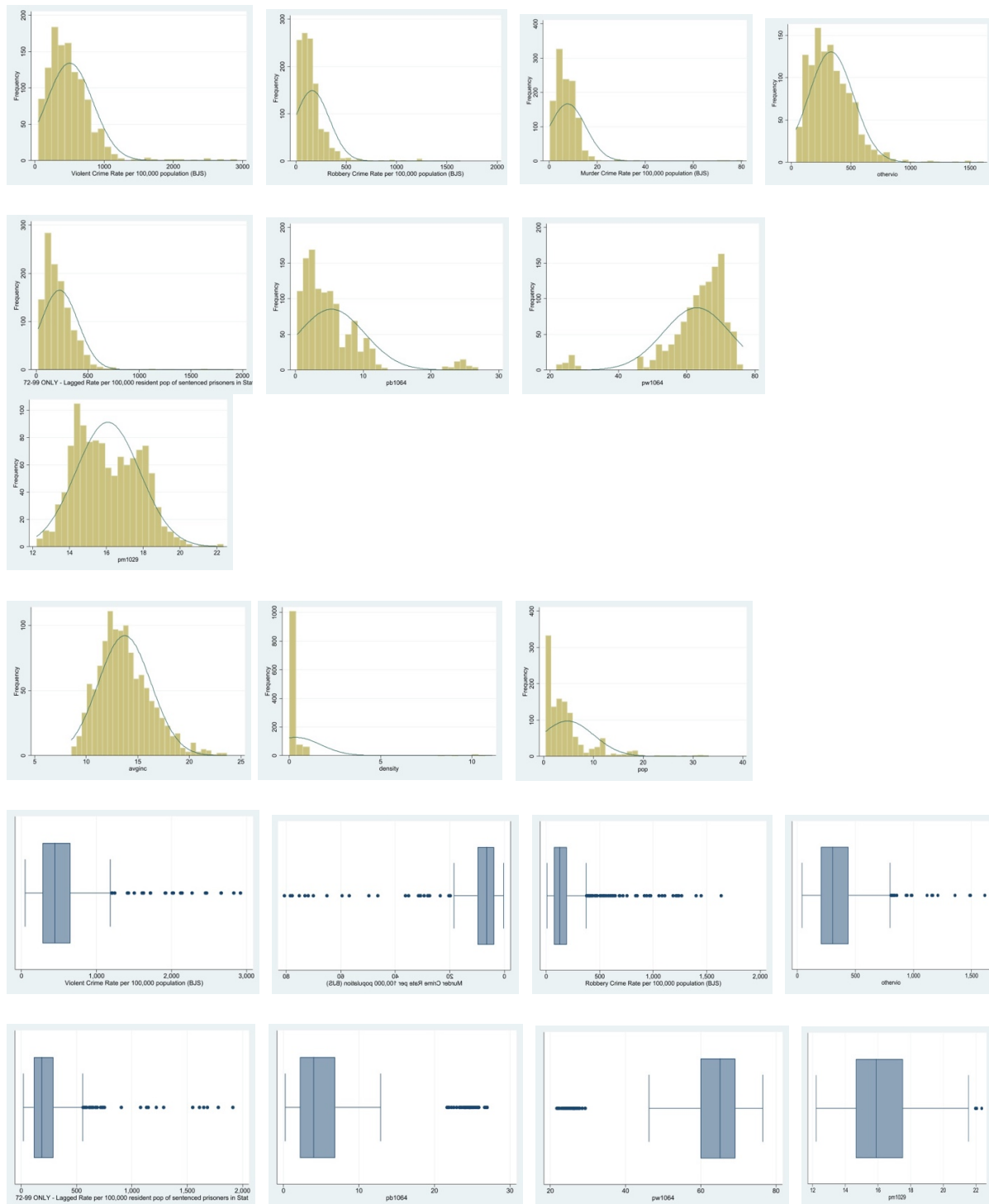
We can observe that on average mur rate is decreased by 3-4%

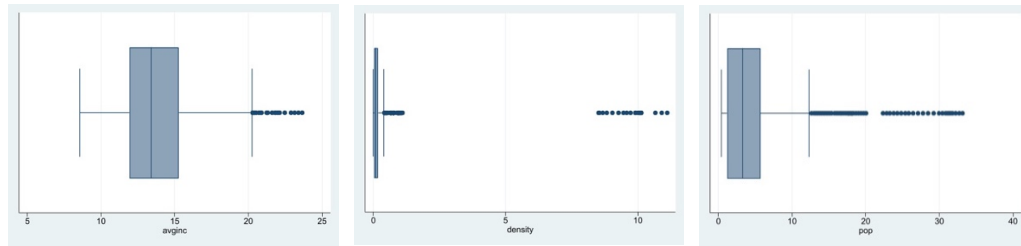
We can observe that on average rob rate is decreased by 1-2%

We can observe that on average othervio rate is decreased by 1-2%

But if we look at the trend we can see that at the last decade ( the average ) values are tending to the same may be in the last decade shall law has no effect but too early to assume let's find out in further study .

### 3.2 Histograms and Box Plots :





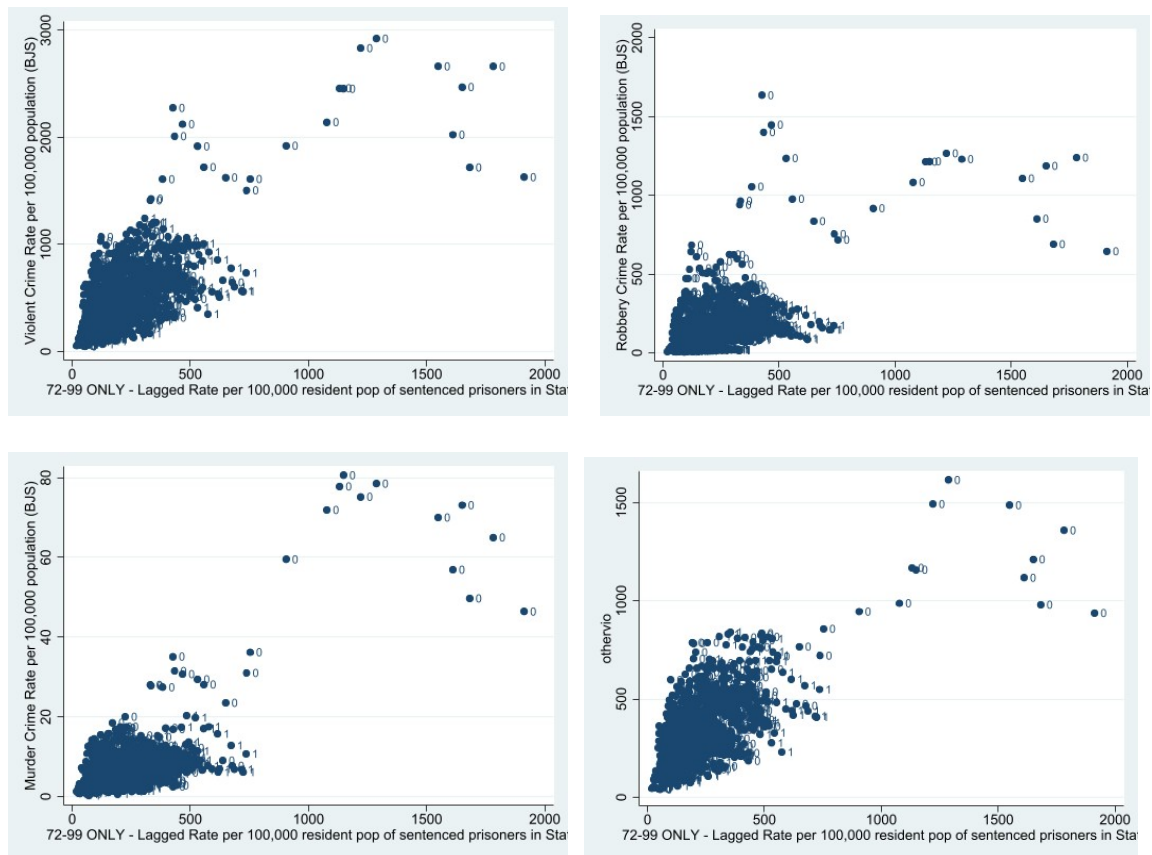
From these plots we can observe that vio, mur, rob, othervio, incarc\_rate, and density are right skewed/Positively skewed and hence we will apply log transformation before we perform the regression .

We can observe that pb1064 and pw1064 data is skewed, where pb1064 is right skewed and pw1064 is left skewed., but we cannot apply transformation but we can transfer these two to indicator variables but it might complex the model so we will leave as is .

Pm1029, avginc and pop are normally distributed and data looks fine from the plots .

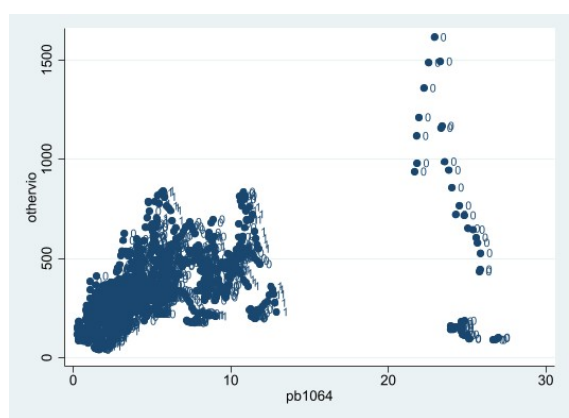
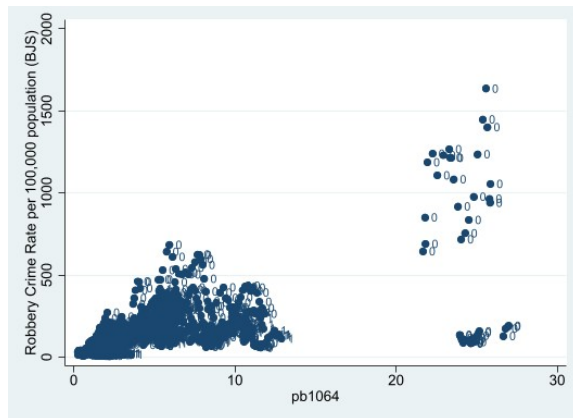
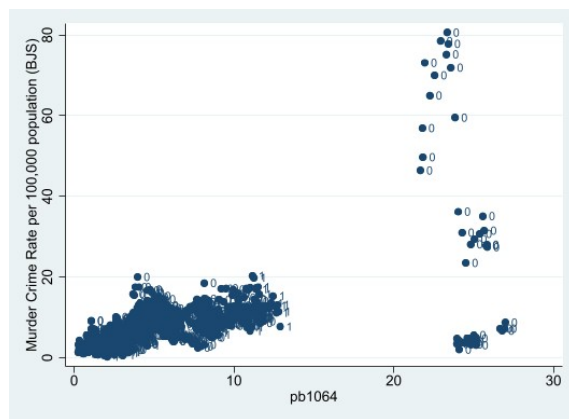
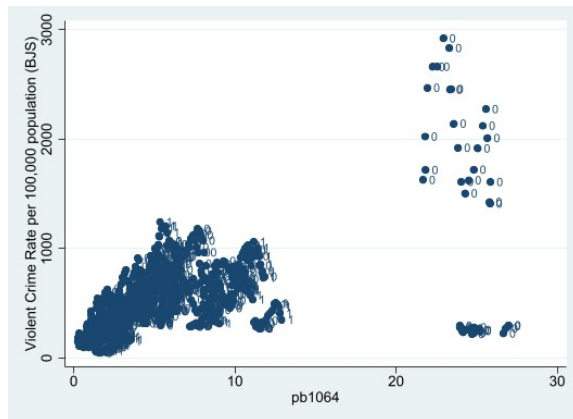
### 3.3 Dependent Variables VS Explanatory Variables w.r.t Shall Law

#### Incrc\_rate & Shall Law



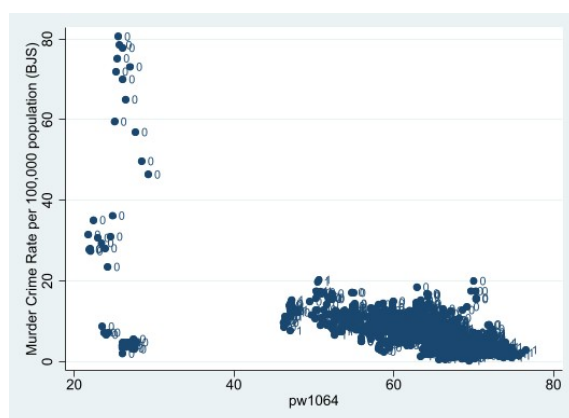
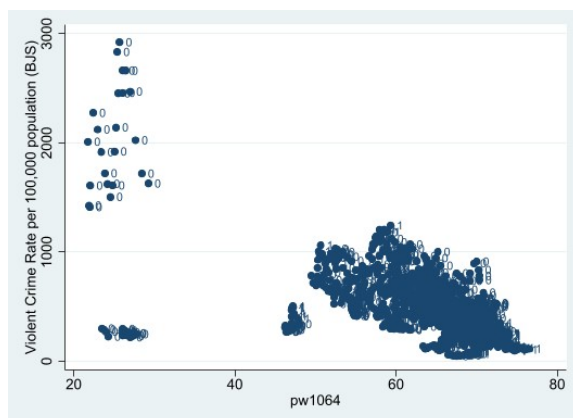
From above we can see that when both incarc\_rate and shall law is in place crimes are controlled when compared when shall law not in place .

## PB1064 & Shall Law:

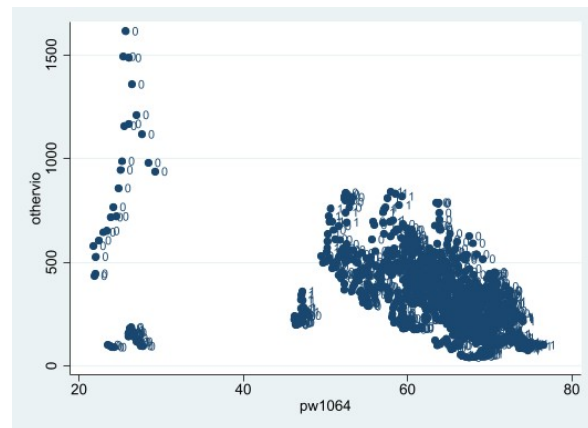
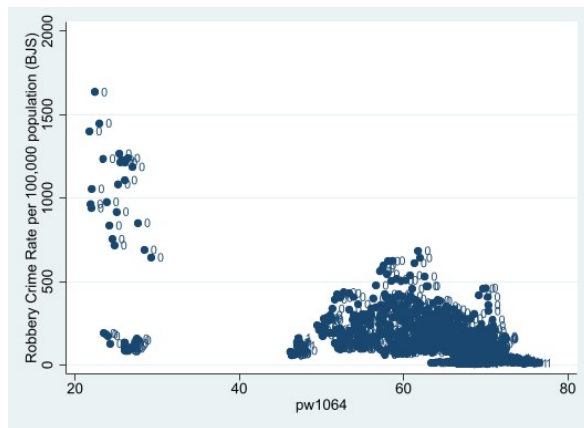


From above we can see that there no much significant impact when percent of state population is 0-10 and we can see that when it is 20-30 it is under control . So shall law can be applied with states having more percentage from this analysis to control crime .

## PW1064 & Shall :

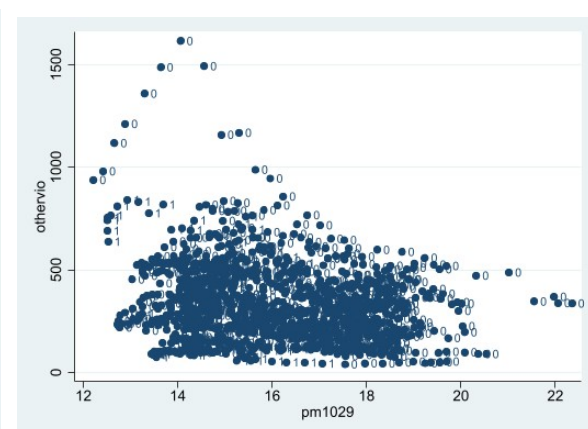
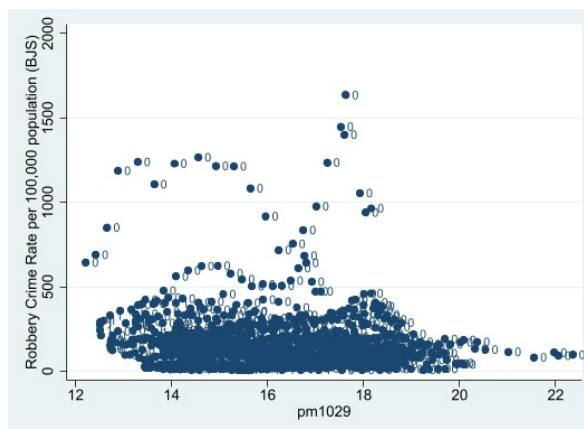
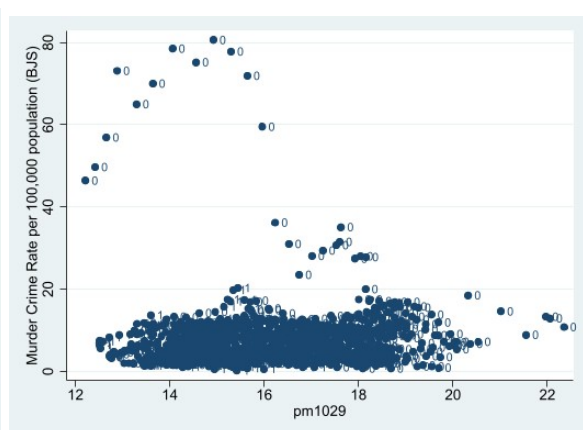
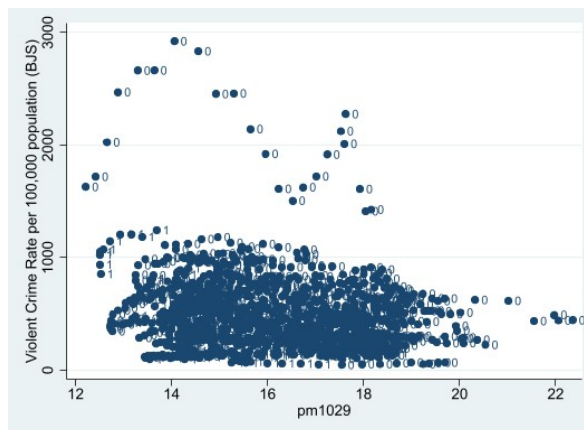






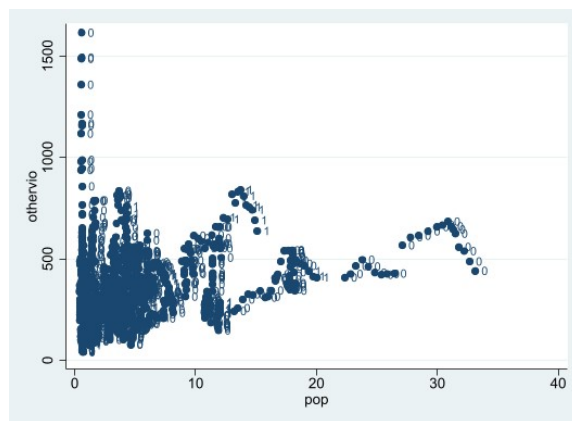
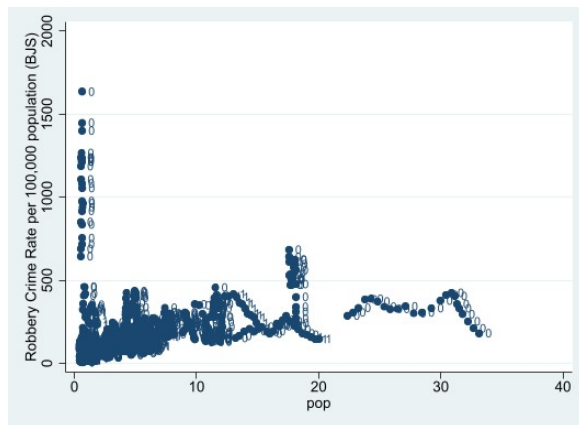
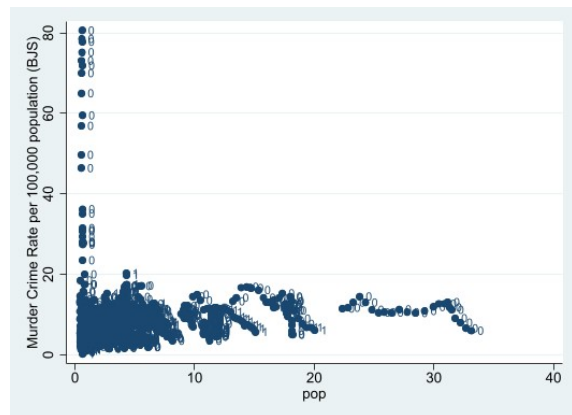
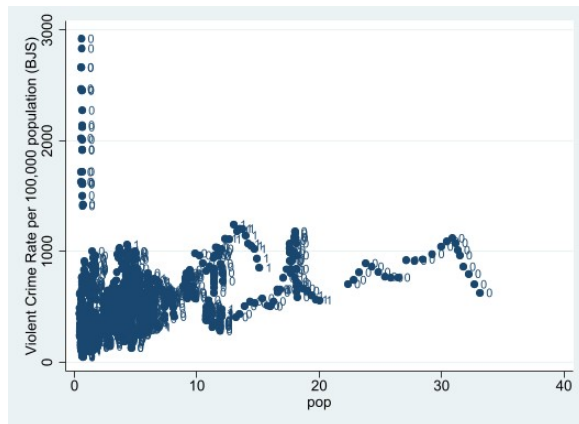
From above we can observe that when the white population is high there is no effect of shall law but when population is high and shall law is not in place crime rates are high so when population is less we can apply shall law to control crime rates .

### Pm1029 & Shall :



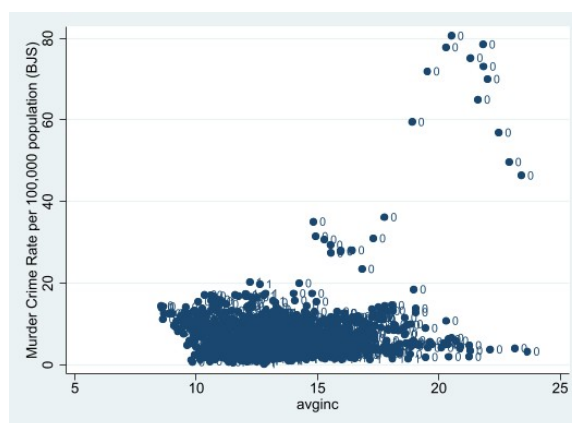
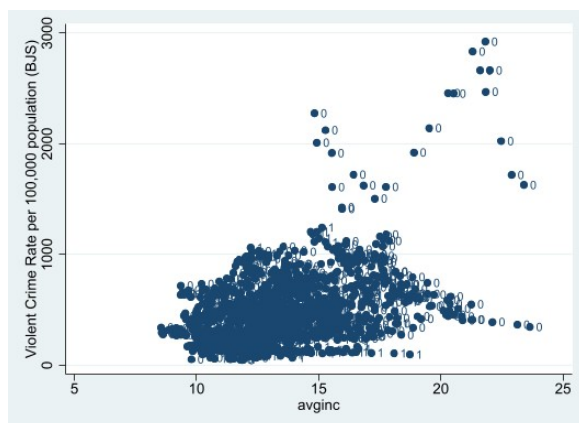
From above we can observe that there is no effect on crimes if population of males increase or decrease and irrespective of the shall in place or not in place .

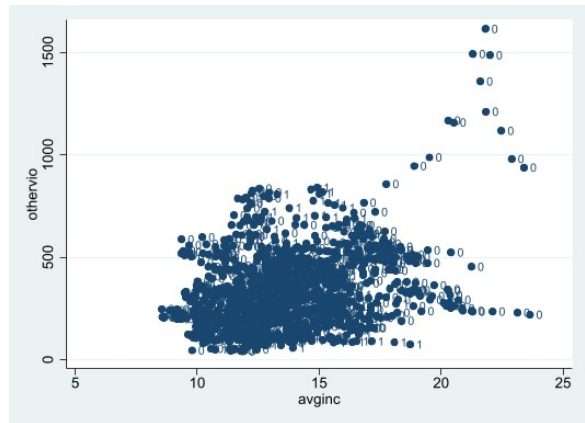
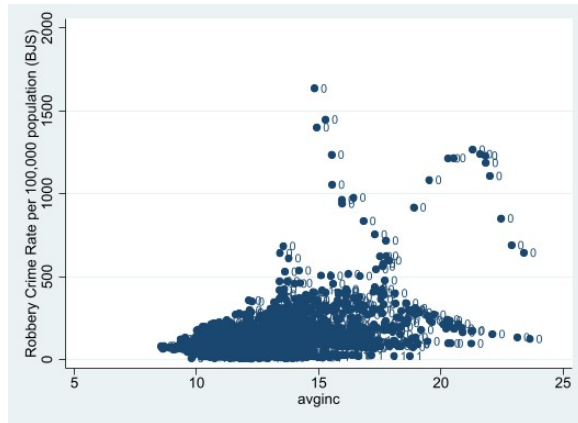
**Pop & shall :**



From above we can observe that crime rates are in control when population increases when shall law is in place .

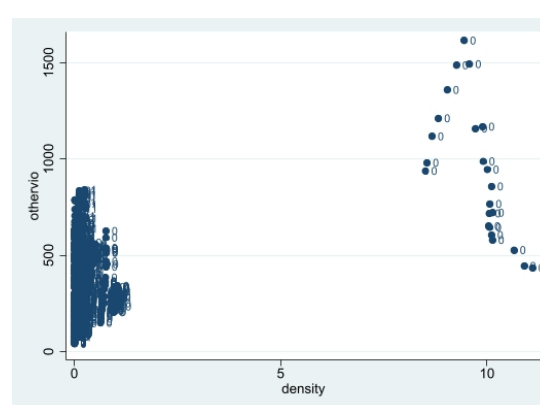
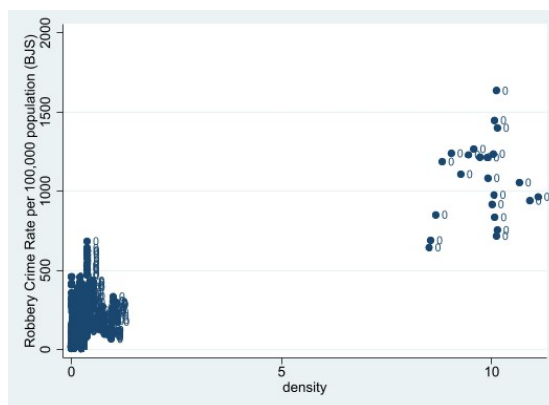
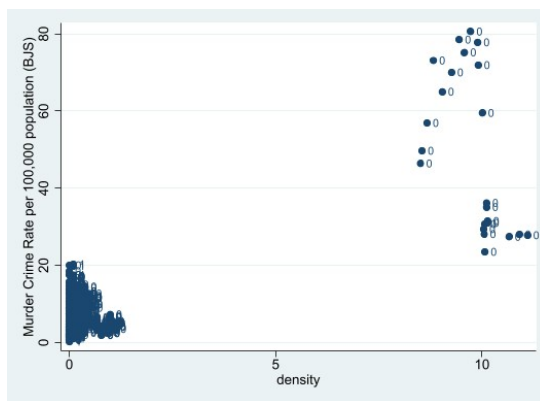
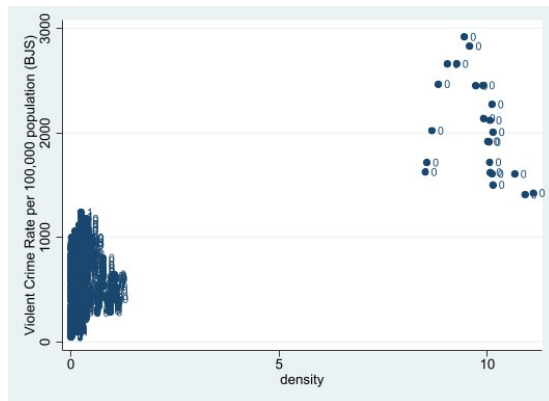
**AVGINC & Shall Law :**





From above we can observe that when avg income increases crime rates tends to down and are in control when shall law is in place when moderate avg income in place .

### Density & Shall :

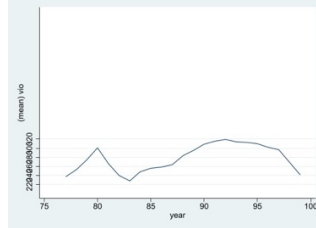


From above we can observe that when density increases and shall law in place crime rates are under control .

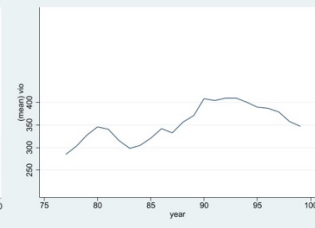
**Different Crimes across states implemented states law in between 77-80,80-85,85-90,90-95,95-99 :**

**Violence rate :-**

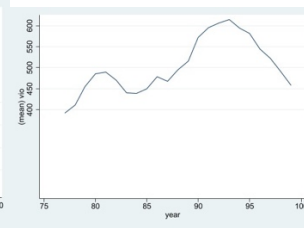
77-80



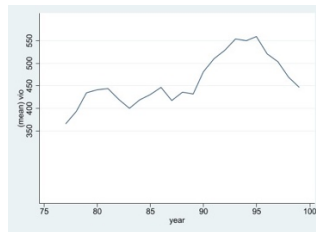
80-85



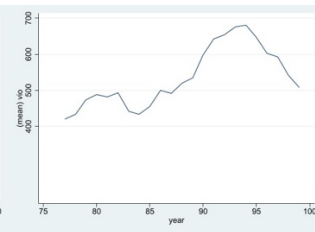
85-90



90-95

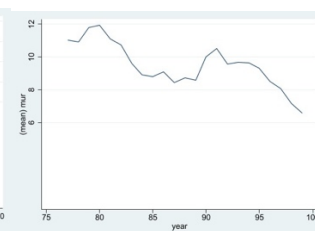
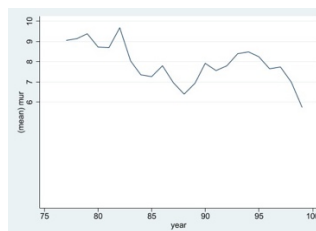
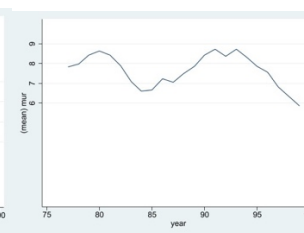
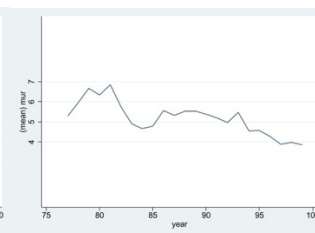
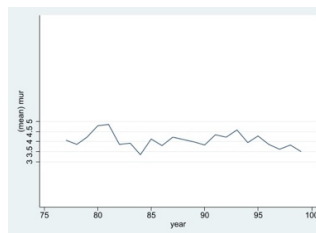


95-99



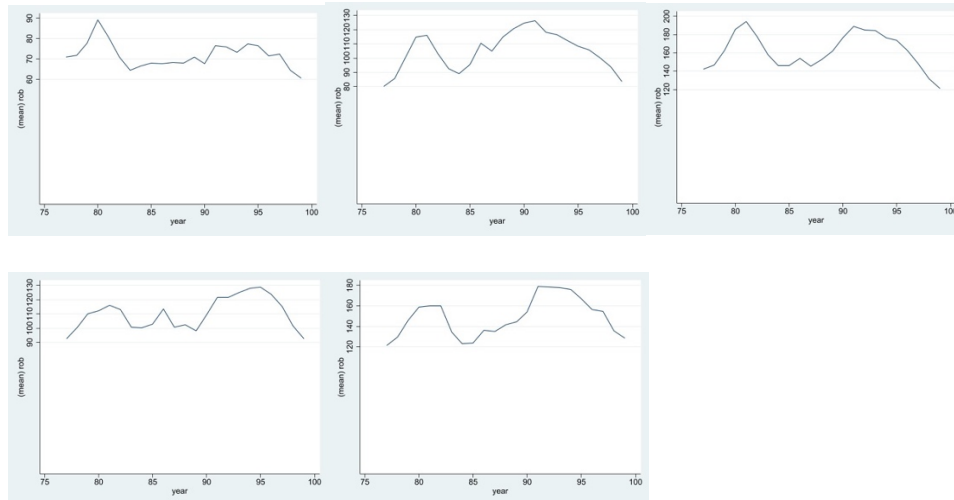
States that have introduced the law in (77–80), (81–85), (86–90) have less average crime rate than states that have introduced shall law in (91–95), (96–100), which shows that states that have adopted the law in the initial period of the observation have less avg. violent rate than the states that implemented the law in the latter period and not sure whether shall law is effective or not .

**Murder rate :-**



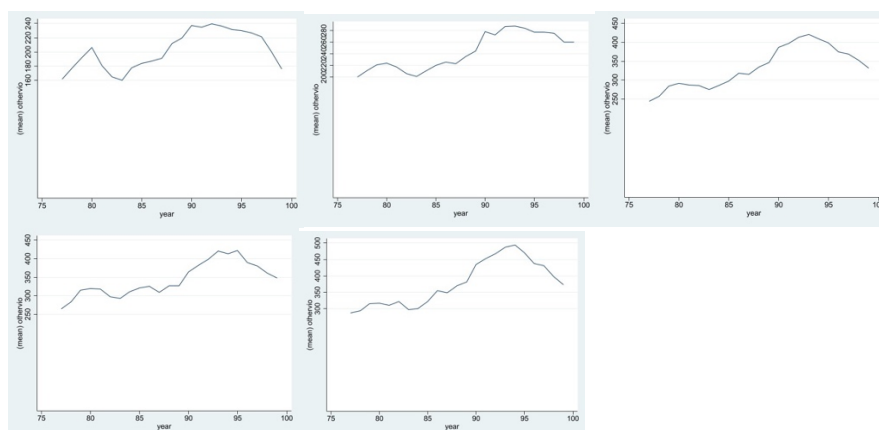
States that have introduced the law in (77–80), (81–85), (86–90) have less average crime rate than states that have introduced shall law in (91–95), (96–100), which shows that states that have adopted the law in the initial period of the observation have less avg. violent rate than the states that implemented the law in the latter period and not sure whether shall law is effective or not .

### Robbery Rate :-



States that have introduced the law in (77–80), (81–85), (86–90) have less average crime rate than states that have introduced shall law in (91–95), (96–100), which shows that states that have adopted the law in the initial period of the observation have less avg. violent rate than the states that implemented the law in the latter period and not sure whether shall law is effective or not .

### Other Violence Rate :-

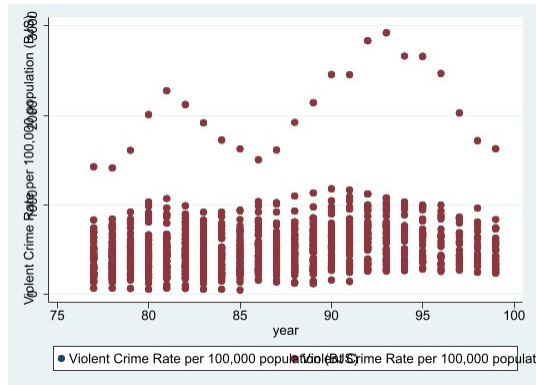


States that have introduced the law in (77–80), (81–85), (86–90) have less average crime rate than states that have introduced shall law in (91–95), (96–100), which shows that states that have adopted the law in the initial period of the observation have less avg. violent rate than

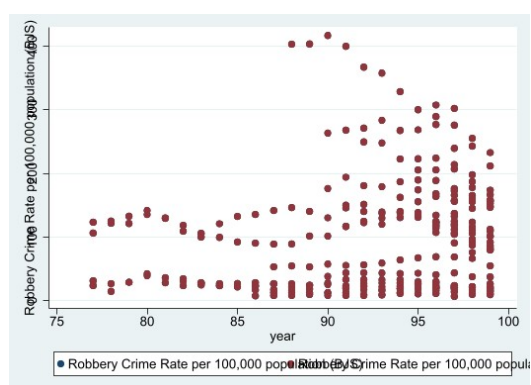
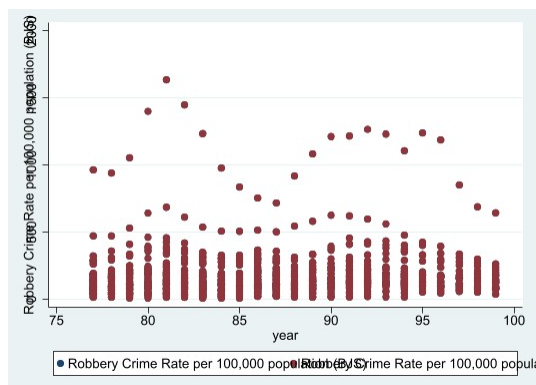
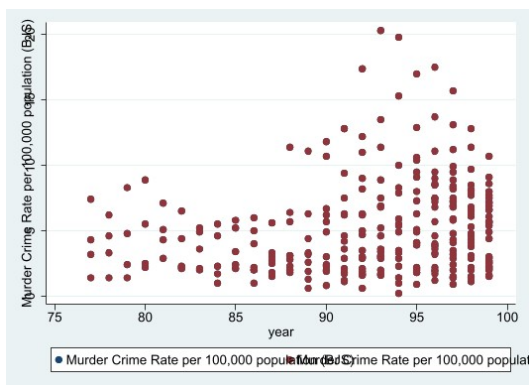
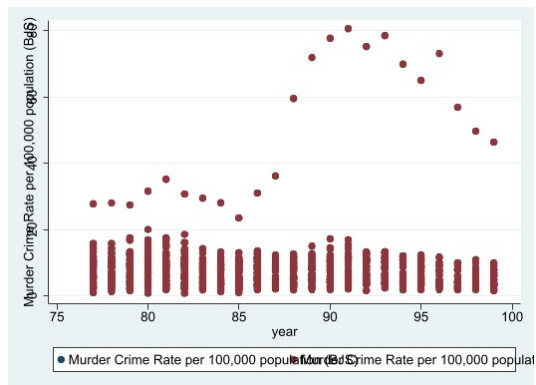
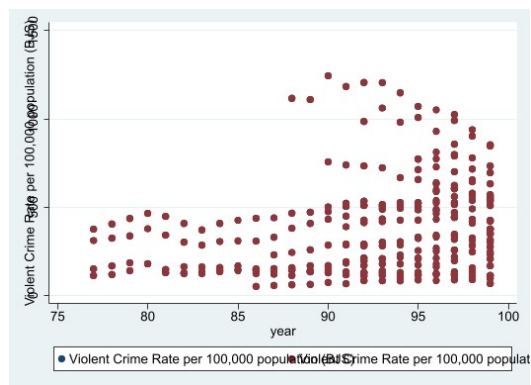
the states that implemented the law in the latter period and not sure whether shall law is effective or not .

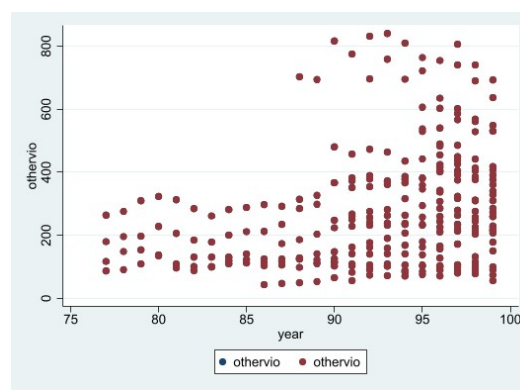
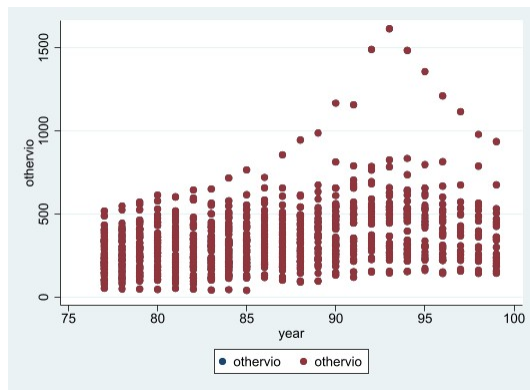
## Crimes YearWise & Shall and No Shall

With No Shall



With Shall

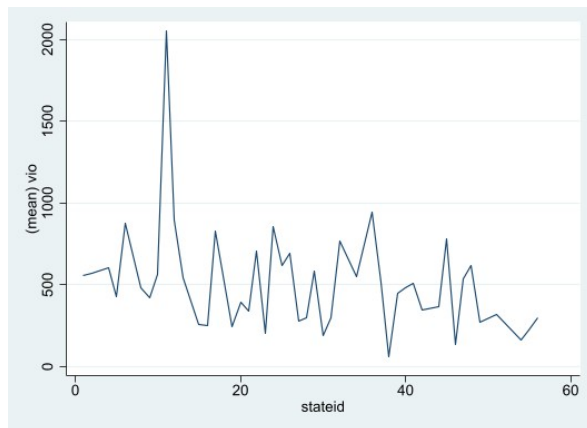




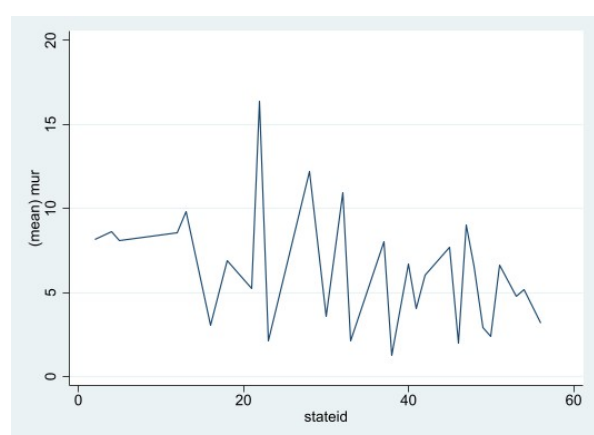
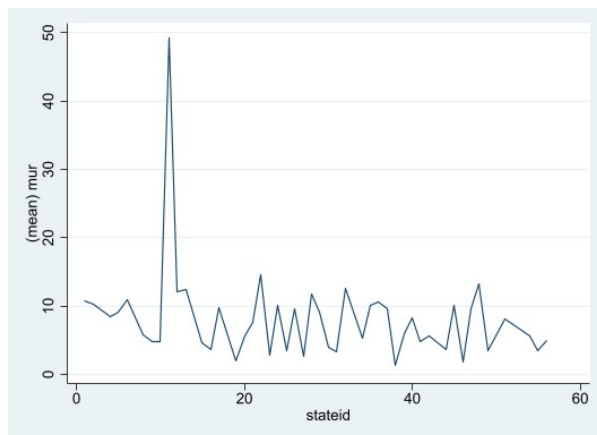
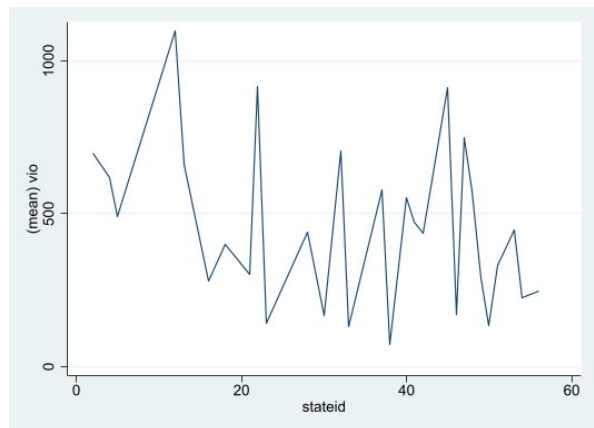
From above trend we can see that when shall law in place the crime rates are under control.

## Crimes Statewise & Shall and No Shall

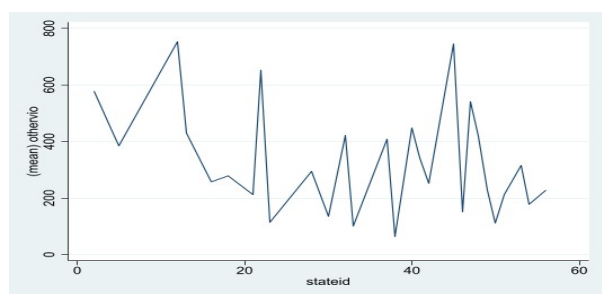
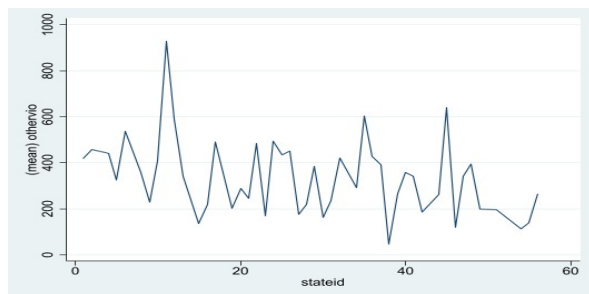
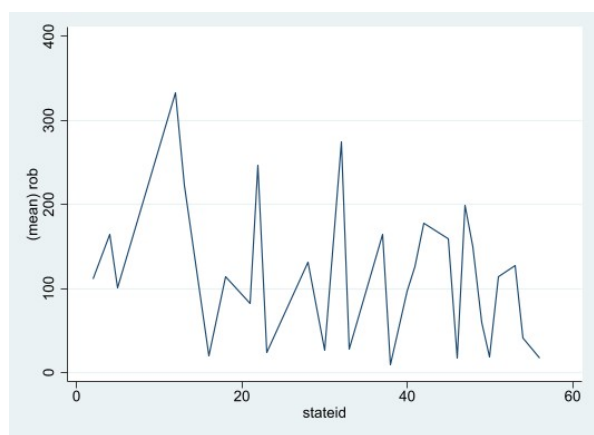
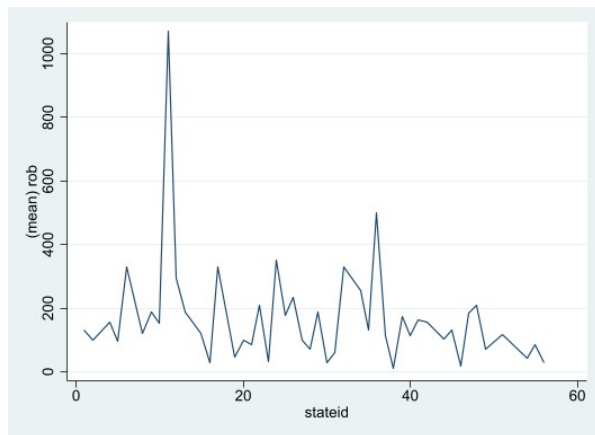
With No Shall



With Shall





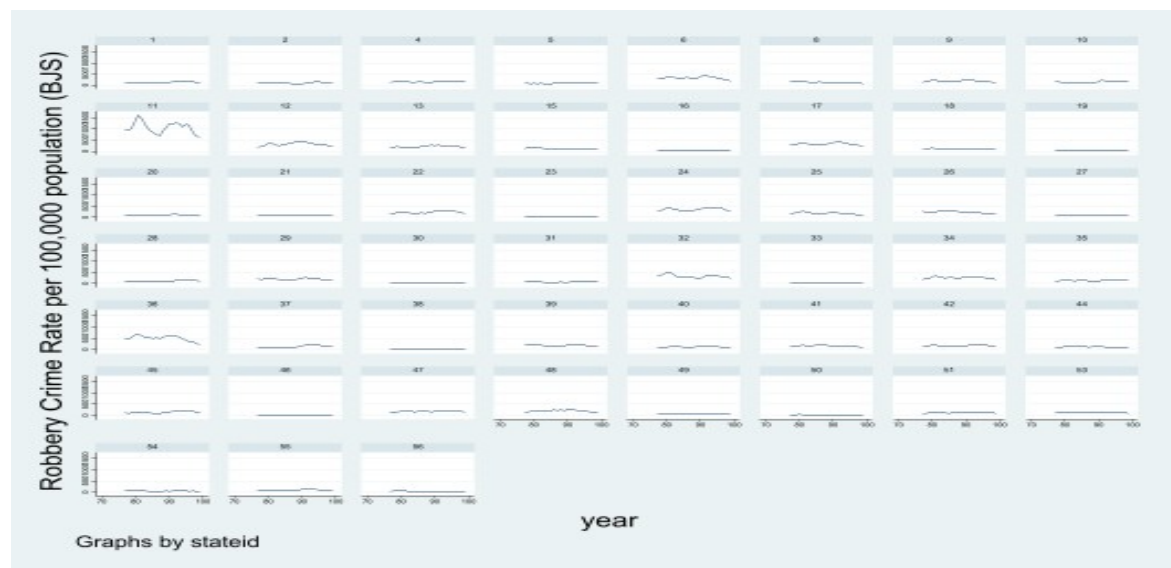
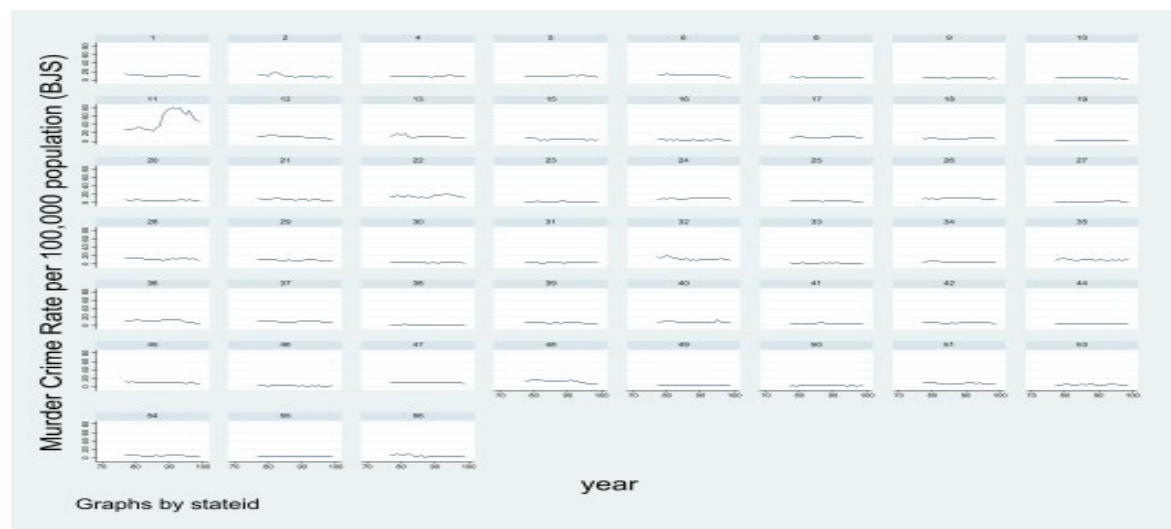
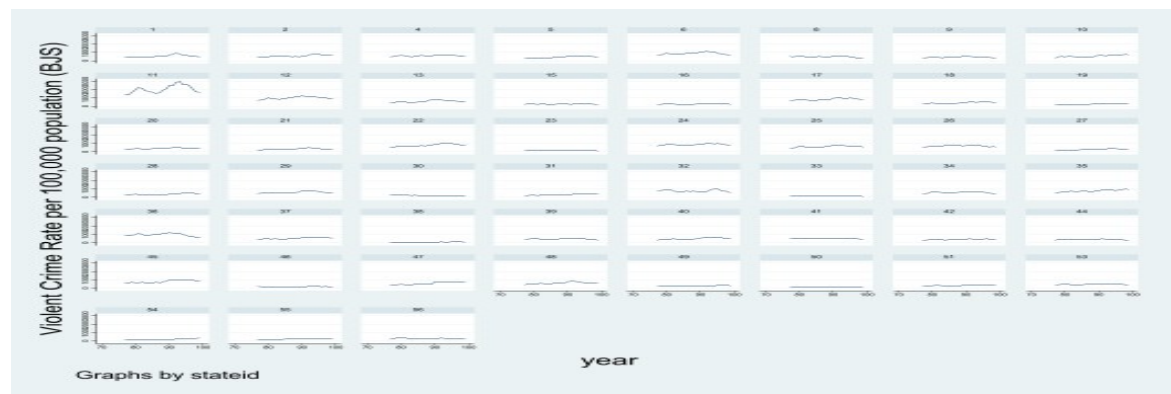


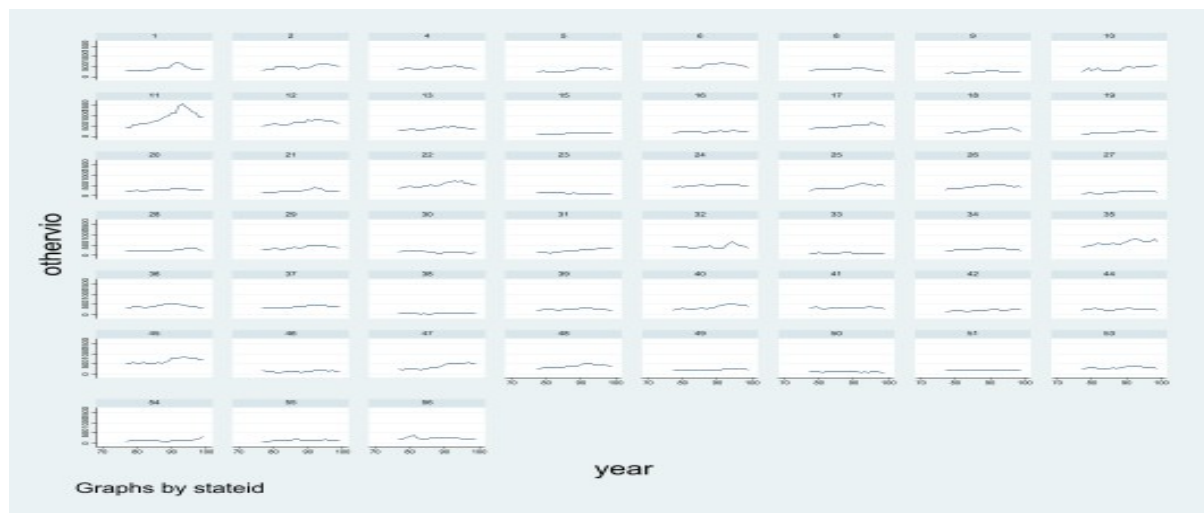
From above overall crimes are controlled across state when shall law is in place and we can see that control is consistent with states means there is no state there is high rate when shall law is not place and low rate or zero when in place it is under control there is no drastic change .

From above we can observe that states with ids 10-20 having crime rates more when compared to other states irrespective of shall and without shall law .

**State, year & Crime :**







From above we can observe that different states has crime rate lower and higher across years irrespective of shall law .

## MODELS

In the provide information we have three different crime rate :- **Violence, Robbery and Murder** , But our study mainly focus on **Violent crime rate** but **we will extend out study to see how Robbery, Murder and Other Violence(vio-(rob+mur))** are controlled using shall law and with other explanatory variables and we can see whether all 4 crime rates are travelling in same direction or in different direction .

Please note that from our analysis we see robbery and murder might be part of violence hence we deduced other vio as  $\text{vio} - (\text{rob} + \text{mur})$  .., we will conclude the same based on our model study if all 4 models are travelling towards same direction and of course our main concentration would be on study of shall law and other explanatory variables across crimes .

**Our main agenda in this section is to:**

- 1) Understand the effect of shall Carry law on the different crime(main focus on violent crime) rate in the US
- 2) Understand how the incarceration rate affects the different crime rate(main focus on violent crime) in the US
- 3) Understand which of the control variables have a significant part in affecting the different crime rate(main focus on violent crime) of the US .

To help us carry out the above goals we run **3 models** to estimate the relationship between the **shall carry law, incarceration rate** together with other **control variables** as **explanatory variables** with the **dependent variable different rate** (main focus on violent crime). Following three models have been run to estimate the relationship between the dependent and the explanatory variables:

1. 1) The Pooled OLS Model
2. 2) The Entity Fixed Effects Model
3. 3) The Time and Entity Fixed Model

To reduce skewness in data to make our statistical inferences/hypothesis correct log transformation has been applied to dependent and explanatory variables .

**Log transformations made:**

**Vio -> log(vio)          mur-> log(mur)          rob -> log(rob)          othervio->log(othervio)**

**Incarc\_rate -> log(incarc\_rate)          density -> log(density) .**

## Expectations based on economic theory :-

1. **Shall** : shall law should be in inverse relation so that when shall law is in place crime rate decreases .
2. **Incarc\_rate** : Incarc\_rate should be in inverse relation which mean if more people are punished or sent to prison in year should reduce the crimes .
3. **Density** : Density is positive relation which means more people in state , crimes can be more .
4. **Average income** : Average income is inversely relation ,which means higher income there should lesser crime .
5. **Pop** : Pop is positively related as population increases we expect crimes go up
6. **Pm1029** : pm1029 is positively related as younger generation commits more crime than older people .
7. **Pw1064** : From the plots we can expect if more white people less crime so it should be negative related .
8. **Pb1064** : From the plots we can expect if more black people more crime so it should be positively related .

## The Pooled OLS Model

The following Pooled OLS Model has been estimated:

$$\log(\text{vio}) = \beta_1 + \beta_2 \log\_incarc_{it} + \beta_3 pb1064_{it} + \beta_4 pw1064_{it} + \beta_5 pm1029_{it} + \beta_6 pop_{it} + \beta_7 avginc_{it} + \beta_8 \log\_density_{it} + \beta_9 shall_{it} + \varepsilon_{it}$$

## Model A Output :-

. reg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc logdensity shall						
Source	SS	df	MS	Number of obs	=	1,173
Model	328.008468	8	41.0010585	F(8, 1164)	=	297.13
Residual	160.623091	1,164	.137992346	Prob > F	=	0.0000
				R-squared	=	0.6713
				Adj R-squared	=	0.6690
Total	488.631558	1,172	.416921125	Root MSE	=	.37147
logvio	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	.6935672	.0252298	27.49	0.000	.6440662	.7430682
pb1064	.0033125	.014386	0.23	0.818	-.0249129	.031538
pw1064	.0033576	.0070293	0.48	0.633	-.0104339	.0171491
pm1029	.1167641	.0102156	11.43	0.000	.096721	.1368071
pop	.0240749	.0023009	10.46	0.000	.0195605	.0285892
avginc	.0232989	.0063738	3.66	0.000	.0107936	.0358042
logdensity	.0928883	.0089614	10.37	0.000	.0753059	.1104707
shall	-.2826839	.0283135	-9.98	0.000	-.338235	-.2271328
_cons	.1816538	.4902108	0.37	0.711	-.7801417	1.143449

## Significant Variable

- shall\_law at all significance level.
- log\_incarc(incarceration rate) at all significance level
- pm1029(percentage of young males) at all significance level
- pop(Population) at all significance levels
- avginc(Average Income) at all significance level
- log\_density(Density) at all significance level

## Insignificant Variable

- pb1064(% population of black people in state)
- pw1064(% population of white people in state)

Test for Significance :-

Ho:-  $\beta_3 = 0, \beta_4 = 0$ , H1 :- Any one is not zero .

```
. test pb1064 pw1064
```

```
( 1) pb1064 = 0
```

```
( 2) pw1064 = 0
```

```
      F( 2, 1164) =    0.69
      Prob > F =    0.5037
```

From Above we can observe that p value > 0.05 so at 5% level we fail to reject the null hypothesis which mean we don't have enough evidence to say that the 2 coefficients are significant .

**Below model B without pb1064 and pw1064**

```
. reg logvio logincarc_rate pm1029 pop avginc shall logdensity
```

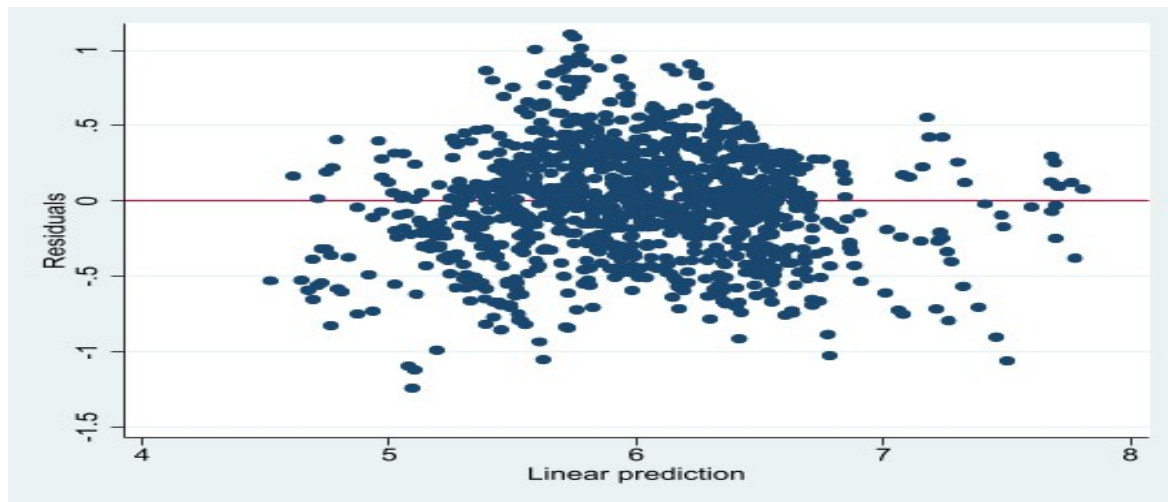
Source	SS	df	MS	Number of obs	=	1,173
Model	327.819114	6	54.6365191	F(6, 1166)	=	396.15
Residual	160.812444	1,166	.137918048	Prob > F	=	0.0000
				R-squared	=	0.6709
				Adj R-squared	=	0.6692
Total	488.631558	1,172	.416921125	Root MSE	=	.37137

logvio	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	.6781481	.0202026	33.57	0.000	.6385106	.7177857
pm1029	.1134168	.0086277	13.15	0.000	.0964893	.1303443
pop	.0245819	.0022304	11.02	0.000	.020206	.0289579
avginc	.0239844	.0053965	4.44	0.000	.0133965	.0345722
shall	-.2780539	.0274432	-10.13	0.000	-.3318975	-.2242102
logdensity	.0880118	.0079309	11.10	0.000	.0724513	.1035723
_cons	.5193309	.2328941	2.23	0.026	.0623926	.9762693

## Test for Heteroskedasticity and Serially Correlated errors :-

Informal test :-



## Formal White Test :-

```
White's test
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

      chi2(43) = 293.46
Prob > chi2 = 0.0000

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

Source	chi2	df	p
Heteroskedasticity	293.46	43	0.0000
Skewness	35.45	8	0.0000
Kurtosis	0.08	1	0.7754
Total	328.99	52	0.0000

From the above two we can say that there is a presence of heteroskedasticity and lets run the model with cluster robust standard errors to correct the standard errors

## Model C with Cluster robust standard Errors :-

```
. reg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc shall logdensity, vce(robust)
```

```
Linear regression              Number of obs   =      1,173
                              F(8, 1164)        =      299.91
                              Prob > F           =      0.0000
                              R-squared          =      0.6713
                              Root MSE       =      .37147
```

logvio	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	.6935672	.0246505	28.14	0.000	.6452028	.7419316
pb1064	.0033125	.016037	0.21	0.836	-.0281521	.0347771
pw1064	.0033576	.0080255	0.42	0.676	-.0123884	.0191036
pm1029	.1167641	.0098848	11.81	0.000	.09737	.1361582
pop	.0240749	.0024971	9.64	0.000	.0191755	.0289742
avginc	.0232989	.0061111	3.81	0.000	.0113088	.0352889
shall	-.2826839	.029917	-9.45	0.000	-.3413811	-.2239867
logdensity	.0928883	.0093021	9.99	0.000	.0746375	.1111391
_cons	.1816538	.5714627	0.32	0.751	-.9395583	1.302866

## Summary for Pooled OLS Model :-

- 1) **Model A** :- Model Estimated that having the right-to-carry law has decreased violence rate by 28% than not having the right-to-carry law .
- 2) Then we conducted formal hypothesis test to check the significance of pb1064 and pw1064 on model and identified they are insignificant .
- 3) **Model B** :- Estimated Model without pb1064,pw1064 and observed that having the right-to-carry law has decreased violence rate by 28% than not having the right-to-carry law .
- 4) Then we checked for serial correlation and heteroskedasticity using informal and formal white test and identified that model is suffering from heteroskedasticity and standard errors has to be corrected using cluster robust standard error .
- 5) **Model C** :- Cluster Robust standard error model is estimated and observed that having the right-to-carry law has decreased violence rate by 28% than not having the right-to-carry law .
- 6) Overall we see pooled OLS has estimated that right-to-carry law has decreased violence rate by 28% but the real effect is much smaller when we did exploratory data analysis, and hence we feel that the estimate is certainly **downwardly biased , hence model is suffering from unobserved heterogeneity which could be like poverty rate or unemployment rate of the people in the state causing more crime rates, causing correlation with error by explanatory variables such as shall leading to a endogeneity problem thus in a process making it downwardly biased as unemployment/poverty is positively correlated with Crime but negative correlated with Shall , thus causing model biased and inconsistent .**
- 7) **Incarc\_rate** as per out expectations it should be **inverse relation** but pooled OLS has identified a **positive relation** which means there could be a **Simultaneous Causality Bias Like more people causing more crime rate and at the same time police are deporting more people for the crimes .**
- 8) **Pm1029,pop,logdensity,pb1064** are in accordance with our expectations .
- 9) **Pw1064** are not in accordance with expectation but we can see that it is not significant at 5% level
- 10) **Average Income** is not in accordance with expectation as we expected to be negatively related but it is vice versa as may suggests of unobserved heterogeneity .
- 11) Comparing Standard error we deduce that

logvio	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	.6935672	.0252298	27.49	0.000	.6440662	.7430682
pb1064	.0033125	.014386	0.23	0.818	-.0249129	.031538
pw1064	.0033576	.0070293	0.48	0.633	-.0104339	.0171491
pm1029	.1167641	.0102156	11.43	0.000	.096721	.1368071
pop	.0240749	.0023009	10.46	0.000	.0195605	.0285892
avginc	.0232989	.0063738	3.66	0.000	.0107936	.0358042
logdensity	.0928883	.0089614	10.37	0.000	.0753059	.1104707
shall	-.2826839	.0283135	-9.98	0.000	-.338235	-.2271328
_cons	.1816538	.4902108	0.37	0.711	-.7801417	1.143449

Robust std. err.	t	P> t	[95% conf. interval]	
.0246505	28.14	0.000	.6452028	.7419316
.016037	0.21	0.836	-.0281521	.0347771
.0080255	0.42	0.676	-.0123884	.0191036
.0098848	11.81	0.000	.09737	.1361582
.0024971	9.64	0.000	.0191755	.0289742
.0061111	3.81	0.000	.0113088	.0352889
.029917	-9.45	0.000	-.3413811	-.2239867
.0093021	9.99	0.000	.0746375	.1111391
.5714627	0.32	0.751	-.9395583	1.302866

When we compare the Standard Errors from OLS and Cluster Robust Model we can observe that for shall law and density the difference are more , hence imply that there are individual characteristics that are not completely captured by the included explanatory variables that are

correlated over time and making pool OLS Model (with robust error) **Inefficient and making model Overstated** .

As mentioned above we suspect the model is biased and inconsistent, to analyze further lets study with Entity Fixed and Time and Entity Fixed Model and deduce further .

## Entity Fixed Model

The following Entity fixed model has been estimated:

$$\log(\text{vio}) = \beta_{1i} + \beta_2 \log\_incarc_{it} + \beta_3 pb1064_{it} + \beta_4 pw1064_{it} + \beta_5 pm1029_{it} + \beta_6 pop_{it} + \beta_7 avginc_{it} + \beta_8 \log\_density_{it} + \beta_9 shall_{it} + \epsilon_{it}$$

Model A output :-

. xtreg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc shall logdensity, fe						
Fixed-effects (within) regression			Number of obs =		1,173	
Group variable: stateid			Number of groups =		51	
R-squared:			Obs per group:			
Within = 0.2236			min =		23	
Between = 0.1068			avg =		23.0	
Overall = 0.0757			max =		23	
			F(8,1114)		= 40.11	
corr(u_i, Xb) = -0.6657			Prob > F		= 0.0000	
logvio	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	-.0672299	.0282092	-2.38	0.017	-.122579	-.0118808
pb1064	.0952893	.0150322	6.34	0.000	.0657947	.1247839
pw1064	.0428067	.0052073	8.22	0.000	.0325894	.053024
pm1029	-.0690675	.0083143	-8.31	0.000	-.0853809	-.052754
pop	.024386	.0092824	2.63	0.009	.0061732	.0425989
avginc	-.0041476	.0057273	-0.72	0.469	-.0153851	.0070899
shall	-.0379066	.0189886	-2.00	0.046	-.075164	-.0006491
logdensity	-.251832	.0859535	-2.93	0.003	-.420481	-.0831831
_cons	3.592115	.4393088	8.18	0.000	2.730149	4.454081
sigma_u	.81282483					
sigma_e	.16012284					
rho	.96264251	(fraction of variance due to u_i)				
F test that all u_i=0: F(50, 1114) = 103.01				Prob > F = 0.0000		

## Significant Variable

- shall\_law at all significance level.
- log\_incarc(incarceration rate) at all significance level
- pm1029(percentage of young males) at all significance level
- pop(Population) at all significance levels
- log\_density(Density) at all significance level
- pb1064(% population of black people in state)
- pw1064(% population of white people in state)

## Insignificant Variable

- average Income is insignificant .



## Model B with Fixed entity model with robust errors to correct the standard errors .

```
. xtreg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc shall logdensity, fe vce(cluster stateid)
```

Fixed-effects (within) regression

Group variable: stateid

Number of obs = 1,173

Number of groups = 51

R-squared:

Within = 0.2236

Between = 0.1068

Overall = 0.0757

Obs per group:

min = 23

avg = 23.0

max = 23

F(8,50) = 5.89

Prob > F = 0.0000

corr(u\_i, Xb) = -0.6657

(Std. err. adjusted for 51 clusters in stateid)

logvio	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]
logincarc_rate	-.0672299	.0690289	-0.97	0.335	-.2058784 .0714187
pb1064	.0952893	.0315747	3.02	0.004	.0318696 .1587089
pw1064	.0428067	.0145712	2.94	0.005	.0135395 .0720739
pm1029	-.0690675	.0257976	-2.68	0.010	-.1208835 -.0172514
pop	.024386	.0119407	2.04	0.046	.0004024 .0483697
avginc	-.0041476	.0131294	-0.32	0.753	-.0305188 .0222236
shall	-.0379066	.0430022	-0.88	0.382	-.124279 .0484659
logdensity	-.251832	.1676589	-1.50	0.139	-.5885848 .0849207
_cons	3.592115	.7697758	4.67	0.000	2.045974 5.138255
sigma_u	.81282483				
sigma_e	.16012284				
rho	.96264251	(fraction of variance due to u_i)			

Test for average Income :-

```
. test avginc
```

( 1) avginc = 0

F( 1, 50) = 0.10

Prob > F = 0.7534

From above test we can say we fail to reject the null hypothesis and at 5% level average income is insignificant .

## Model C without Average Income

```
. xtreg logvio logincarc_rate pb1064 pw1064 pm1029 pop shall logdensity, fe vce (cluster stateid)
```

Fixed-effects (within) regression

Group variable: stateid

Number of obs = 1,173

Number of groups = 51

R-squared:

Within = 0.2233

Between = 0.1087

Overall = 0.0771

Obs per group:

min = 23

avg = 23.0

max = 23

F(7,50) = 7.06

Prob > F = 0.0000

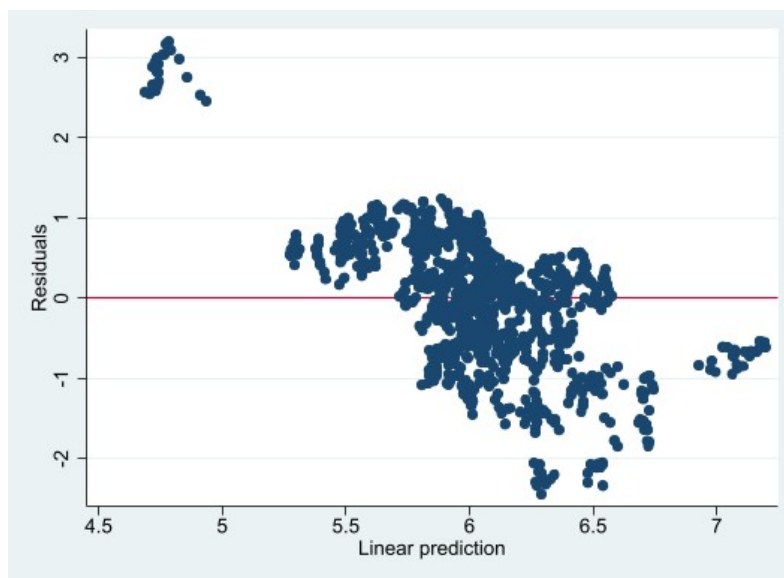
corr(u\_i, Xb) = -0.6658

(Std. err. adjusted for 51 clusters in stateid)

logvio	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]
logincarc_rate	-.0726068	.0664483	-1.09	0.280	-.2060721 .0608584
pb1064	.0940313	.0306698	3.07	0.003	.0324293 .1556333
pw1064	.0425889	.0145957	2.92	0.005	.0132725 .0719052
pm1029	-.0672519	.0244447	-2.75	0.008	-.1163505 -.0181534
pop	.0241646	.011653	2.07	0.043	.0007589 .0475703
shall	-.0380101	.0429559	-0.88	0.380	-.1242896 .0482694
logdensity	-.2503523	.1668377	-1.50	0.140	-.5854557 .0847511
_cons	3.559252	.7664323	4.64	0.000	2.019827 5.098677
sigma_u	.81222128				
sigma_e	.16008869				
rho	.96260441	(fraction of variance due to u_i)			

## Summary for Entity Fixed Model :-

- 1) **Model A** :- Fixed Entity Model Estimated without robust standard error that, having the right-to-carry law has decreased violence rate by 3.7% than not having the right-to-carry law .
- 2) **Model B** :- Fixed Entity Model Estimated with robust standard error that, having the right-to-carry law has decreased violence rate by 3.7% than not having the right-to-carry law .
- 3) Then we conducted formal hypothesis test to check the significance of average income on model and identified it is insignificant .
- 4) **Model C** :- Fixed Entity Model Estimated with robust standard error without average income variable that, having the right-to-carry law has decreased violence rate by 3.8% than not having the right-to-carry law .
- 5) **Incarc\_rate** is as per our expectation it is in inverse relation with crime rate .
- 6) **Pm1029,pop,logdensity,pb1064,pw1064** are in accordance with our expectations .
- 7) **Average Income** is in accordance with expectation but the formal test suggested it is an insignificant variable .
- 8) Check for heteroskedasticity :-



Not much of coned or inverted u shape suggests that there is no heteroskedasticity in the estimated model .

By using Fixed Entity model we identified **unbiased and consistent estimator** , because it explains the variation over time with in entities i.e., states but cannot explain the **variation of target and explanatory variables over time across entities i.e., states or variation across entities but constant over time** .

In order to make unbiased, consistent and efficient estimator we will use **Time And Entity Fixed Model**

## Time And Entity Fixed Model

$$\begin{aligned} \text{Log(vio)} = & \beta_0 + \beta_1 \log\_incarc_{it} + \beta_2 pb1064_{it} + \beta_3 pw1064_{it} + \beta_4 pm1029_{it} + \beta_5 pop_{it} + \\ & \beta_6 avginc_{it} + \beta_7 \log\_density_{it} + \beta_8 shall_{it} \\ & + \delta_2 factor\_year78_{it} + \delta_3 factor\_year79_{it} + \delta_4 factor\_year80_{it} \\ & + \delta_5 factor\_year81_{it} + \delta_6 factor\_year82_{it} + \delta_7 factor\_year83_{it} \\ & + \delta_8 factor\_year84_{it} + \delta_9 factor\_year85_{it} + \delta_{10} factor\_year86_{it} + \\ & \delta_{11} factor\_year87_{it} + \delta_{12} factor\_year88_{it} + \delta_{13} factor\_year89_{it} + \\ & \delta_{14} factor\_year90_{it} + \delta_{15} factor\_year91_{it} + \delta_{16} factor\_year92_{it} + \\ & \delta_{17} factor\_year93_{it} + \delta_{18} factor\_year94_{it} + \delta_{19} factor\_year95_{it} + \\ & \delta_{20} factor\_year96_{it} + \delta_{21} factor\_year97_{it} + \delta_{22} factor\_year98_{it} + \\ & \delta_{23} factor\_year99_{it} + u_{it} \end{aligned}$$

## Model Output :-

### Without standard robust error :

```
. xtreg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc shall logdensity i.year, fe
```

Fixed-effects (within) regression	Number of obs	=	1,173
Group variable: stateid	Number of groups	=	51
R-squared:	Obs per group:		
Within = 0.4256	min	=	23
Between = 0.2521	avg	=	23.0
Overall = 0.1791	max	=	23
	F(30,1092)	=	26.97
corr(u_i, Xb) = -0.7920	Prob > F	=	0.0000

	logvio	Coefficient	Std. err.	t	P> t	[95% conf. interval]
logincarc_rate		-.1042005	.0281708	-3.70	0.000	-.1594756 -.0489254
pb1064		-.0116159	.0196878	-0.59	0.555	-.050246 .0270142
pw1064		-.0012751	.0076177	-0.17	0.867	-.0162221 .0136719
pm1029		.0790354	.0154122	5.13	0.000	.0487945 .1092763
pop		.0060215	.0083075	0.72	0.469	-.0102788 .0223219
avginc		.0018515	.0062919	0.29	0.769	-.010494 .014197
shall		-.0280295	.0172992	-1.62	0.105	-.0619729 .005914
logdensity		-.2539255	.0768528	-3.30	0.001	-.4047213 -.1031297
year						
78		.0676702	.0280068	2.42	0.016	.012717 .1226233
79		.1865317	.028683	6.50	0.000	.1302517 .2428117
80		.2485785	.0292264	8.51	0.000	.1912323 .3059247
81		.2569276	.0304912	8.43	0.000	.1970997 .3167555
82		.2505044	.0327855	7.64	0.000	.1861746 .3148342
83		.2292094	.0358749	6.39	0.000	.1588179 .299601
84		.2715517	.0397885	6.82	0.000	.1934812 .3496222
85		.3302087	.0435107	7.59	0.000	.2448346 .4155828
86		.4184033	.0478227	8.75	0.000	.3245685 .5122381
logdensity		-.2539255	.0768528	-3.30	0.001	-.4047213 -.1031297
year						
78		.0676702	.0280068	2.42	0.016	.012717 .1226233
79		.1865317	.028683	6.50	0.000	.1302517 .2428117
80		.2485785	.0292264	8.51	0.000	.1912323 .3059247
81		.2569276	.0304912	8.43	0.000	.1970997 .3167555
82		.2505044	.0327855	7.64	0.000	.1861746 .3148342
83		.2292094	.0358749	6.39	0.000	.1588179 .299601
84		.2715517	.0397885	6.82	0.000	.1934812 .3496222
85		.3302087	.0435107	7.59	0.000	.2448346 .4155828
86		.4184033	.0478227	8.75	0.000	.3245685 .5122381
87		.4274345	.052169	8.19	0.000	.3250717 .5297972
88		.4992313	.0569334	8.77	0.000	.3875201 .6109425
89		.5644762	.0613829	9.20	0.000	.4440344 .684918
90		.7010562	.0743982	9.42	0.000	.5550765 .8470359
91		.7656106	.0780946	9.80	0.000	.6123781 .9188431
92		.8085042	.082475	9.80	0.000	.6466768 .9703315
93		.8406783	.0856934	9.81	0.000	.6725359 1.008821
94		.8368897	.0895086	9.35	0.000	.6612615 1.012518
95		.8428252	.0933387	9.03	0.000	.6596817 1.025969
96		.7985925	.0970704	8.23	0.000	.6081268 .9890581
97		.787869	.1006015	7.83	0.000	.5904749 .985263
98		.7426846	.1046289	7.10	0.000	.5373882 .947981
99		.693198	.1081344	6.41	0.000	.4810233 .9053728
_cons		4.243414	.4896784	8.67	0.000	3.282597 5.204231
sigma_u		.94152993				
sigma_e		.13910999				
rho		.97863663	(fraction of variance due to u_i)			

F test that all u\_i=0: F(50, 1092) = 123.48      Prob > F = 0.0000

## With Robust Standard Error :

. xtreg logvio logincarc_rate pb1064 pw1064 pm1029 pop avginc shall logdensity i.year, fe vce(cluster stateid)						
Fixed-effects (within) regression			Number of obs	=	1,173	
Group variable: stateid			Number of groups	=	51	
R-squared:			Obs per group:			
Within = 0.4256			min	=	23	
Between = 0.2521			avg	=	23.0	
Overall = 0.1791			max	=	23	
			F(30,50)	=	50.65	
corr(u_i, Xb) = -0.7920			Prob > F	=	0.0000	
(Std. err. adjusted for 51 clusters in stateid)						
logvio	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
logincarc_rate	-.1042005	.0701137	-1.49	0.144	-.245028	.036627
pb1064	-.0116159	.0518888	-0.22	0.824	-.1158377	.0926059
pw1064	-.0012751	.02644	-0.05	0.962	-.0543814	.0518312
pm1029	.0790354	.0542966	1.46	0.152	-.0300225	.1880933
pop	.0060215	.0132625	0.45	0.652	-.020617	.03266
avginc	.0018515	.016111	0.11	0.909	-.0305084	.0342114
shall	-.0280295	.0393915	-0.71	0.480	-.1071496	.0510907
logdensity	-.2539255	.1934079	-1.31	0.195	-.6423967	.1345458
year						
78	.0676702	.0162234	4.17	0.000	.0350845	.1002558
79	.1865317	.0279303	6.68	0.000	.130432	.2426314
80	.2485785	.0398247	6.24	0.000	.1685882	.3285687
81	.2569276	.0441591	5.82	0.000	.1682314	.3456238
82	.2505044	.0552367	4.54	0.000	.1395581	.3614506
83	.2292094	.0683524	3.35	0.002	.0919195	.3664994
84	.2715517	.0836701	3.25	0.002	.1034954	.439608
85	.3302087	.0991093	3.33	0.002	.1311418	.5292756
86	.4184033	.1156434	3.62	0.001	.1861267	.6506799
87	.4274345	.1327176	3.22	0.002	.1608633	.6940056
88	.4992313	.1477365	3.38	0.001	.2024938	.7959688
89	.5644762	.1624827	3.47	0.001	.23812	.8908324
90	.7010562	.2107014	3.33	0.002	.2778501	1.124262
91	.7656106	.2205978	3.47	0.001	.3225269	1.208694
92	.8085042	.2334615	3.46	0.001	.3395831	1.277425
93	.8406783	.2436728	3.45	0.001	.3512471	1.33011
94	.8368897	.2525728	3.31	0.002	.3295823	1.344197
95	.8428252	.2644269	3.19	0.002	.3117082	1.373942
96	.7985925	.2765084	2.89	0.006	.2432089	1.353976
97	.787869	.2843986	2.77	0.008	.2166375	1.3591
98	.7426846	.2966396	2.50	0.016	.1468665	1.338503
99	.693198	.3071174	2.26	0.028	.0763345	1.310062
_cons	4.243414	1.159203	3.66	0.001	1.915085	6.571743
sigma_u	.94152993					
sigma_e	.13910999					
rho	.97863663	(fraction of variance due to u_i)				

## Significant Variable

None at 5% level of significance which is expected when we use time and fixed effects but at 15% we have shall law, incarc\_rate, pm1029

## Insignificant Variable

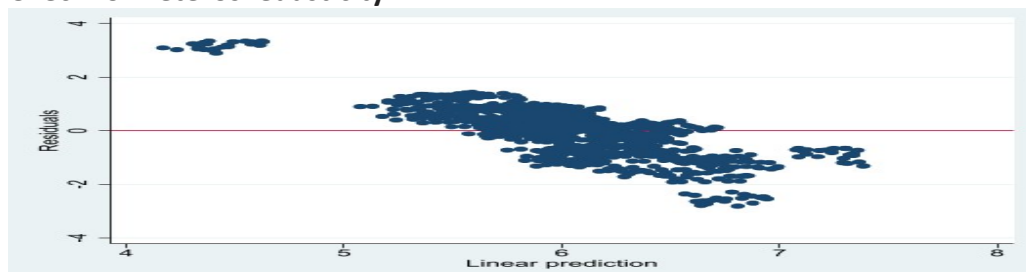
- All other explanatory variables are insignificant .

## Significance test for year

```
. 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) = 21.15  
Prob > F = 0.0000
```

From the above test we can say that we reject the null hypothesis and say that year parameter is significant at 5% level of significance .

## Check for heteroskedasticity :



Above plot we can say that there is no inverted u shape or cone shape so that we can say that there is no heteroskedasticity exists .

## Summary for Entity Fixed Model :-

- 1) **Model** :- Time and Entity Fixed Model Estimated with robust standard error that, having the right-to-carry law has decreased violence rate by 2.8% than not having the right-to-carry law .
- 2) Then we conducted formal hypothesis test to check the significance of year param on model and identified it is significant .
- 3) Check for heteroskedasticity :- Above plot we can say that there is no inverted u shape or cone shape so that we can say that there is no heteroskedasticity exists .

## Conclusion :

- Estimate of both “Fixed Effects with entity-fixed and time-fixed” and “Fixed effects with entity-fixed” model shows that having right-to-carry law has reduced violent crime rate than not having right-to-carry law but only by less than 3~4% .
- We can observe that the p-values are significant at 10% when we didn’t use robust standard error .
- We can say that `incarc_rate` is also reducing the crime rates like 1% increase in `incarc_rate` reduces crime rate by 0.1% which is significant at 5% when we don’t use robust standard error which is not to a greater extent .

## Other Crimes study :-

We will check the other crimes study to make our initial assumptions like violence rate has subset of murder and crime and all three travel in same direction of magnitude over shall law .

## Murder Rate :-

```
. estimate table olsmur femur tfemur
```

Variable	olsmur	femur	tfemur
<code>logincarc_ve</code>	.73628244	-.15924099	-.09737396
<code>pb1064</code>	.03984465	-.02347342	-.07477117
<code>pw1064</code>	.00764987	.01440054	-.01213434
<code>pm1029</code>	.16617375	.00387808	.07267798
<code>pop</code>	.02288696	-.00882476	-.0220534
<code>avginc</code>	-.04209353	.0378963	.06559448
<code>shall</code>	-.21724231	-.05643298	-.01826872
<code>logdensity</code>	.07522799	-.37070118	-.27564665

Above comparison study says that when shall law in place we can say that murder rate is reduced by 1.8% and `incarc_rate` also contributing reduction on crime rate by 9% .

## Robbery Rate :-

```
. estimate table olsrob ferob tferob
```

Variable	olsrob	ferob	tferob
logincarc_~e	.61599673	-.19891984	-.22108639
pb1064	.042355	.10982811	-.02112381
pw1064	.01494163	.03614011	-.021238
pm1029	.16001255	-.02581845	.11422541
pop	.04728032	.01898272	-.00288926
avginc	.04741071	-.00411044	.01634256
shall	-.41786691	-.01274975	.00849535
logdensity	.2307483	.07399156	.04993624

Above comparison study says that when shall law in place we can say that robbery rate is increased by 0.8% and incarc\_rate reduces robbery crime rate by 0.22% . This is blown out of proportion shall law has no effect in reduction of robberies , but sending people to jail has a big reduction of robbery rate so in order to reduce robberies more people who committed crime should be sent to jail .

## Other Violence Rate :-

```
. estimate table olsothervio feothervio tfeothervio
```

Variable	olsother~o	feothervio	tfeother~o
logincarc_~e	.75168617	.01868212	-.0421034
pb1064	-.02209121	.02439221	-.09954946
pw1064	-.00339542	.03167461	-.01861435
pm1029	.09952356	-.07617584	.09541296
pop	.01563815	.03549443	.01497463
avginc	.01175961	.01412865	.01302674
shall	-.2409245	-.05286935	-.05044761
logdensity	.04425778	-.38246089	-.40116315

Above comparison study says that when shall law in place we can say that other violence rate is reduced by 5% and incarc\_rate reduces robbery crime rate by 0.04% .