

# DO MORE GUNS AND /OR HIGHER INCARCERATION REDUCE CRIME?

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## Data Description & Data Analysis

The data provided (guns.dta) is panel in nature. It comprised of 50 states in United States of America and included District of Columbia tallying up to 51 states over a time period of 23 years (1977 - 1999). By looking at the data first, it looked like there were states missing with the states codes '3', '4', '14' and '43'. Upon further investigation it was identified that these states codes do not exist. From basic understanding it looked like states with Shall law implemented would have lower violence rates. However, this was not the case, there were states with higher violence rate when Shall Law was implemented.

Analysis of the data throughout the project was performed using STATA, R and SAS programming.

Summary of the data –

year	vio	mur	rob
Min. :77	Min. : 47.0	Min. : 0.200	Min. : 6.4
1st Qu.:82	1st Qu.: 283.1	1st Qu.: 3.700	1st Qu.: 71.1
Median :88	Median : 443.0	Median : 6.400	Median : 124.1
Mean :88	Mean : 503.1	Mean : 7.665	Mean : 161.8
3rd Qu.:94	3rd Qu.: 650.9	3rd Qu.: 9.800	3rd Qu.: 192.7
Max. :99	Max. :2921.8	Max. :80.600	Max. :1635.1

incarc_rate	pb1064	pw1064	pm1029
Min. : 19.0	Min. : 0.2482	Min. :21.78	Min. :12.21
1st Qu.: 114.0	1st Qu.: 2.2022	1st Qu.:59.94	1st Qu.:14.65
Median : 187.0	Median : 4.0262	Median :65.06	Median :15.90
Mean : 226.6	Mean : 5.3362	Mean :62.95	Mean :16.08
3rd Qu.: 291.0	3rd Qu.: 6.8507	3rd Qu.:69.20	3rd Qu.:17.53
Max. :1913.0	Max. :26.9796	Max. :76.53	Max. :22.35

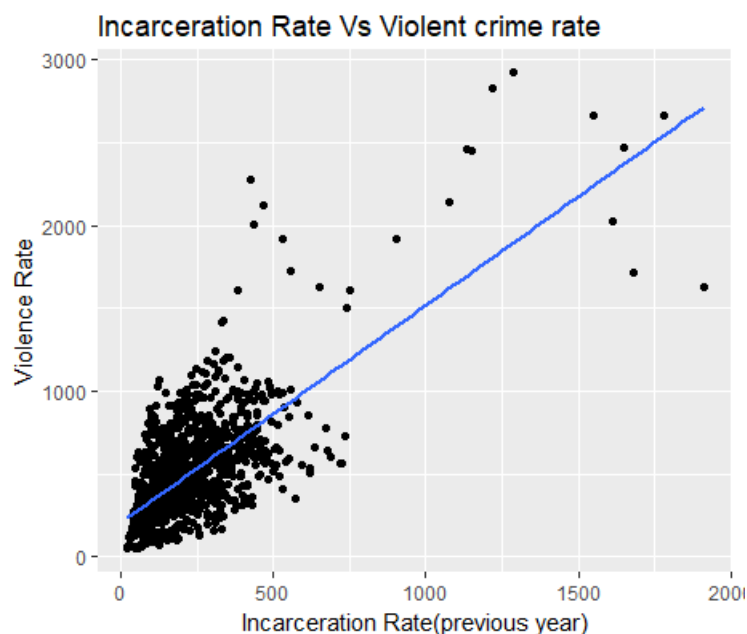
  

pop	avginc	density	stateid
Min. : 0.4027	Min. : 8.555	Min. : 0.000707	Min. : 1.00
1st Qu.: 1.1877	1st Qu.:11.935	1st Qu.: 0.031911	1st Qu.:16.00
Median : 3.2713	Median :13.402	Median : 0.081569	Median :29.00
Mean : 4.8163	Mean :13.725	Mean : 0.352038	Mean :28.96
3rd Qu.: 5.6856	3rd Qu.:15.271	3rd Qu.: 0.177718	3rd Qu.:42.00
Max. :33.1451	Max. :23.647	Max. :11.102116	Max. :56.00

From the above statistics we get a vague idea of the range and level of data we are dealing with.

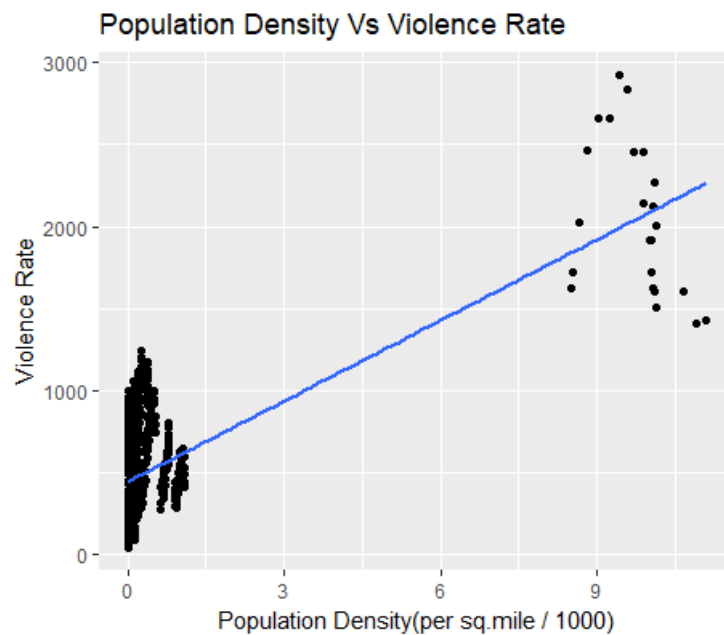
The following insights were found when we performed exploratory analysis on the data –

### **1. Incarceration rate Vs violent crime rate**



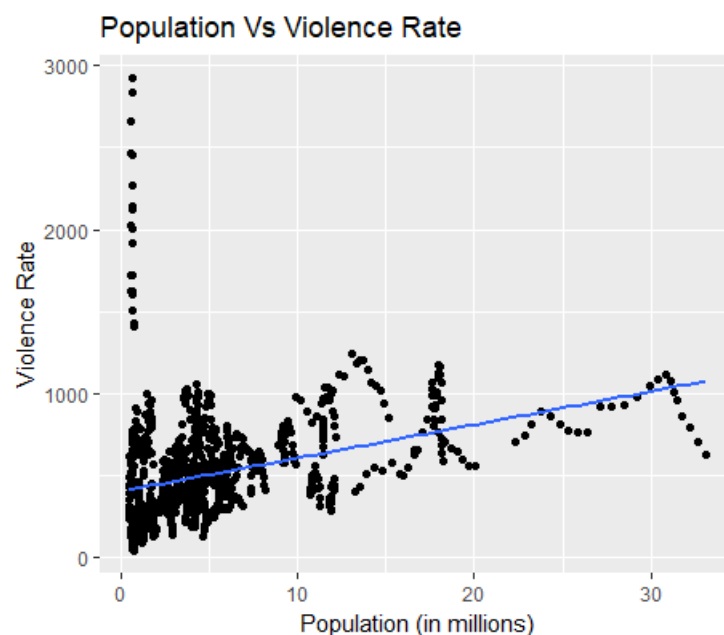
From the above graph it can be seen that there is a positive relationship between incarceration rate and violent crime rate (incidents per 100,000 members of the population). For majority of the cases, as crime rate increases incarceration rate also increases.

## 2. Population density Vs violent crime rate



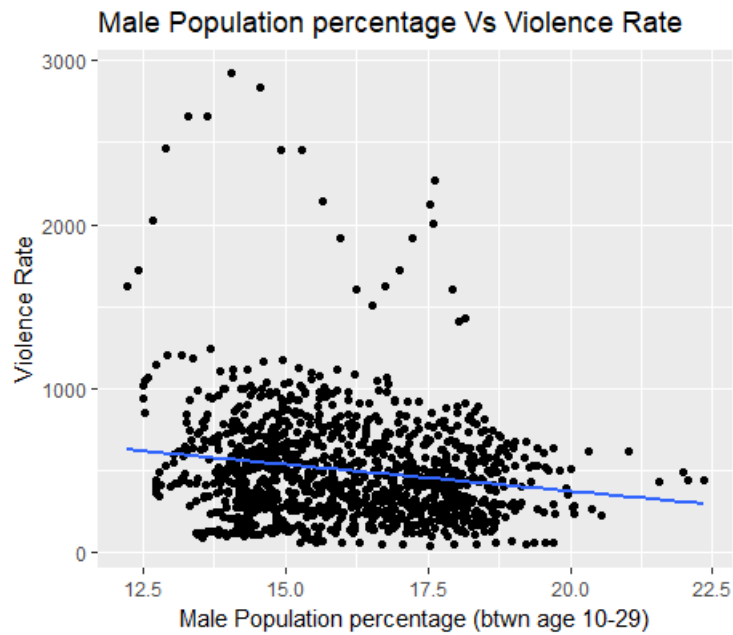
In the above graph violence rate is plotted against population density (population per square mile of land area, divided by 1000). Here as well, we could say there is a positive trend between the 2 variables. Very high violent crime rate exists where the population density is also very high.

## 3. Population Vs violent crime rate



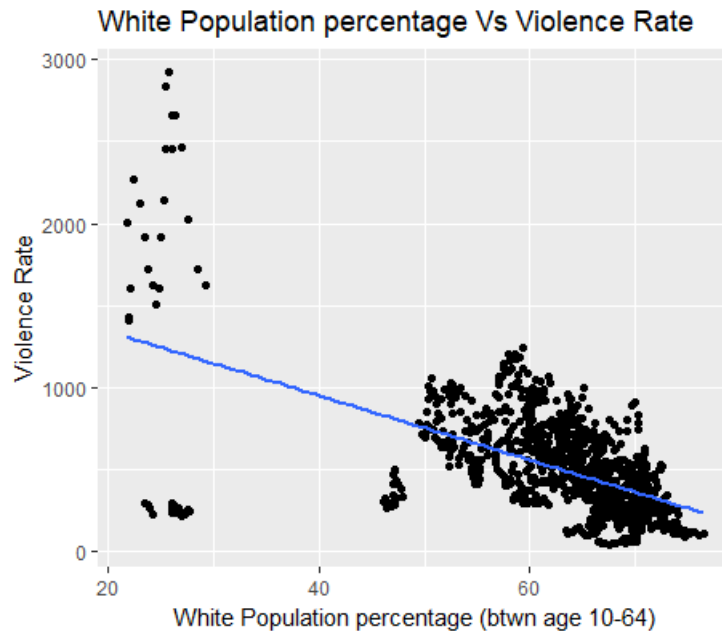
In the above graph violent crime rate is plotted against population. Crime rate increases as population increases. There are a few states where violence rate is high even though population is less.

#### 4. pm1029 vs violent crime rate



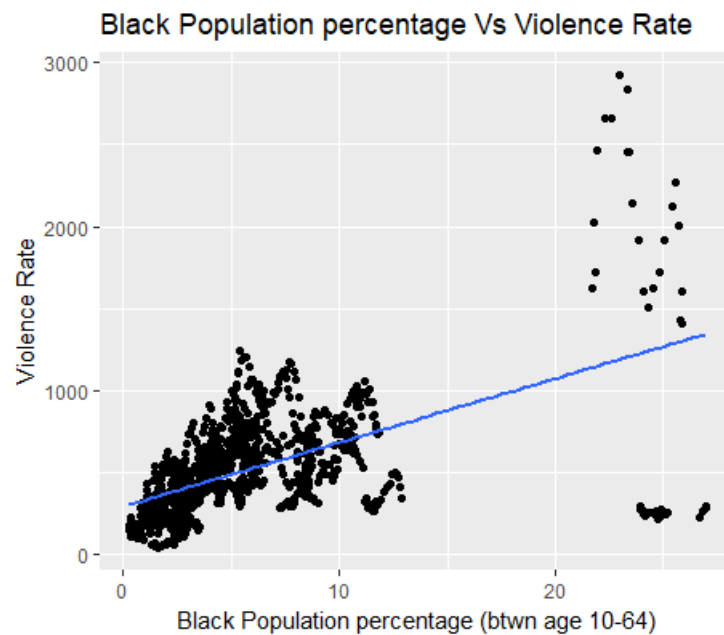
In the above graph violent crime rate is plotted against male population percentage in the age group of 10 to 29. The graph doesn't show a high correlation between these variables.

#### 5. pw1064 Vs violent crime rate



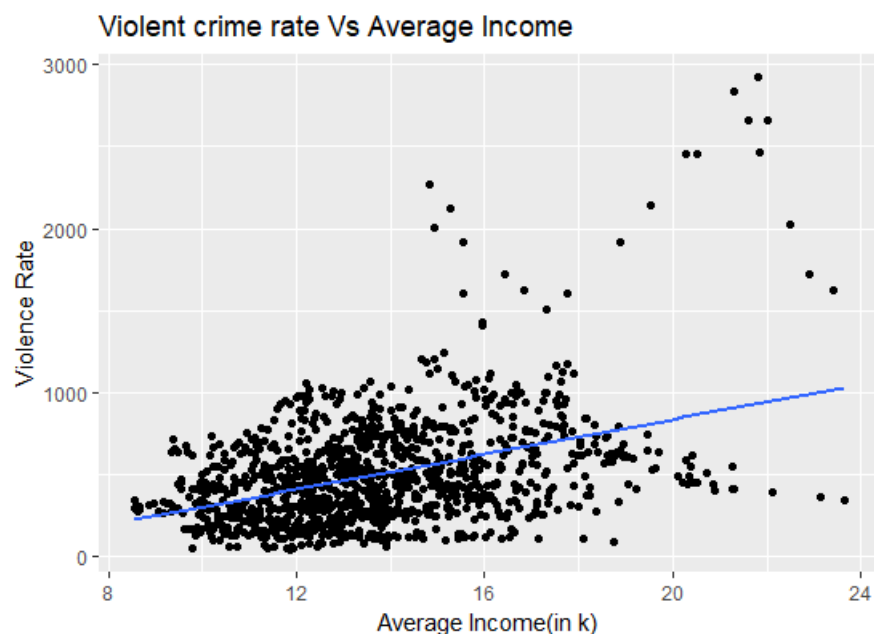
In the above graph violent crime rate is plotted against the white population percentage in the age bracket of 10 to 64. The graph shows that as the white population percentage is higher in that state, violent crime rate declines. This is a very interesting insight and an area we would love to dig deeper into.

## 6. pb1064 Vs violent crime rate



In the above graph, violent crime rate is plotted against black population percentage in the ages of 10 to 64. This is the exact opposite scenario of white population percentage vs violent crime rate (lateral flip in the graphs). This graph shows that as black population percentage increases, the violent crime rate seems to also increase. From economic theory the wages of black people when compared to white is comparatively lower, due to this they might be staying in a dangerous neighbourhood.

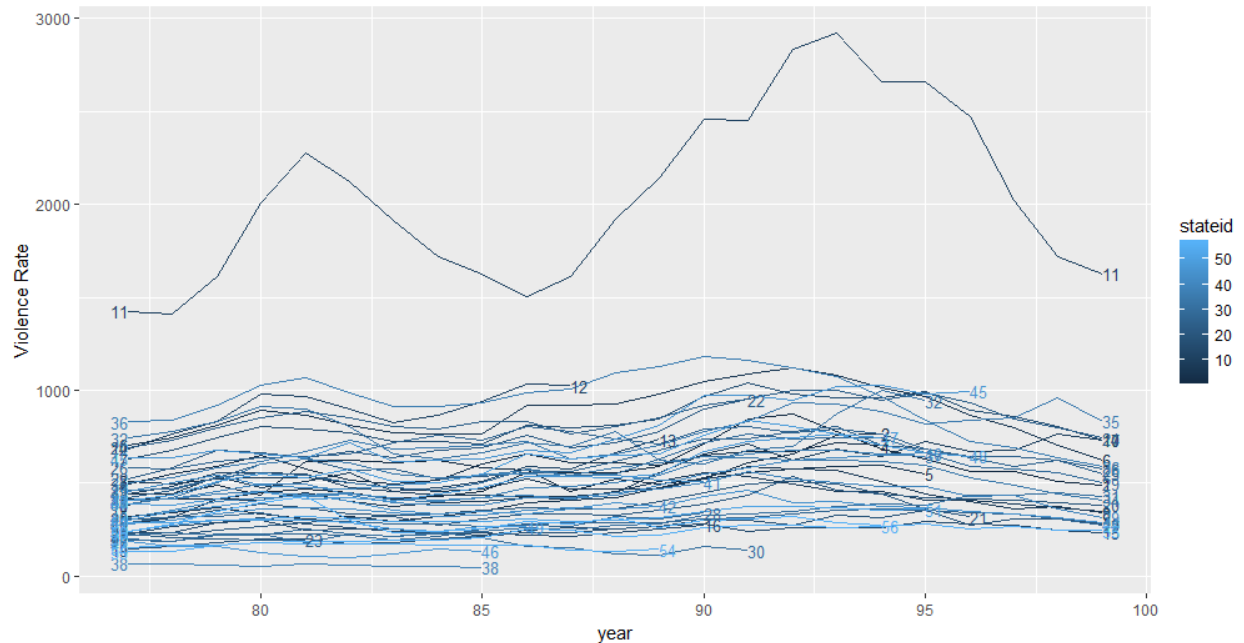
## 7. Violent crime rate Vs average income



In the above graph violent crime rate is plotted against average per capita personal income of the state (in thousands of dollars). Here again we can observe that states with higher average per capita personal income have lower crime rates indicating that the neighbourhood is safer (people with higher pay wouldn't indulge in crime related activities) when compared to lower income states. However, some states with high average income seems to have higher violent crime rate. This maybe because richer people also face a risk of getting attacked.

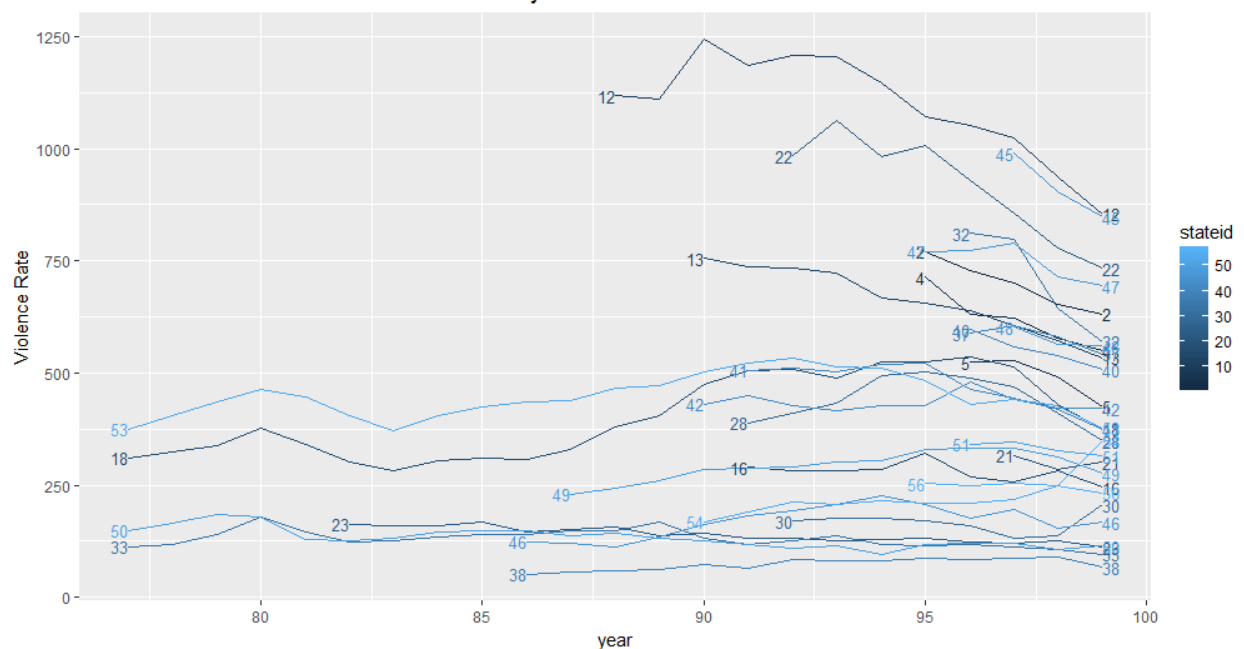
## 8. Comparing state wise violent crime rate based on shall-carry law

State wise violent crime Rate when Shall-carry law isn't in effect



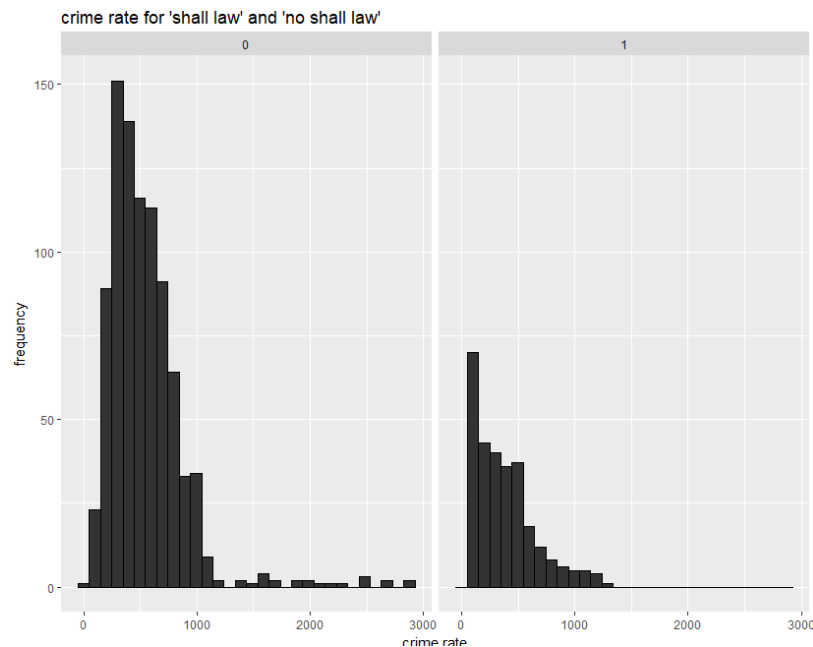
The above graph plots the state wise violent crime rate when Shall-carry law isn't in effect. The state id 11 (District of Columbia) seems to have an exceptionally high violent crime rate when compared to other states when the shall-carry law wasn't implied. State id 38 (North Dakota) seems to have the lowest violent crime rate even though data is available till 1985 only.

State wise violent crime Rate when Shall-carry law is in effect



The above graph plots the state wise violent crime rate when Shall-carry law is in effect. Violent rate seems to be lesser in the states where shall-carry law is in effect. With the shall law implemented, Florida (12) seems to still have a high violent crime rate and North Dakota continues to have the least violent crime rate amongst all other states.

Now we shift our focus towards Shall Law. We have performed several comparison analyses of crime rate against shall law. Below are further insights specific to shall law –



Side by side comparison of violent crime rate when shall law was implemented and when it wasn't.

#### Violent Rate with respect to Shall law:

hr\$shall: 0						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
47.0	315.0	478.4	542.2	676.4	2921.8	
-----						
hr\$shall: 1						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
51.3	149.5	322.0	381.1	514.6	1244.3	

Shall: 0, no shall law

Shall: 1, shall law present in the state

#### Murder Rate with respect to Shall law:

hr\$shall: 0						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
0.700	4.200	7.400	8.429	10.400	80.600	
-----						
hr\$shall: 1						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
0.200	2.300	4.600	5.284	7.300	20.300	

Shall: 0, no shall law

Shall: 1, shall law present in the state

#### Robbery Rate with respect to Shall law:

hr\$shall: 0						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
6.4	85.9	133.8	182.3	210.6	1635.1	
-----						
hr\$shall: 1						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	
6.4	23.3	86.6	97.9	141.4	416.8	

Shall: 0, no shall law

Shall: 1, shall law present in the state

It looks like shall law does influence the respective crime rates. We see general drop in crime rates when shall law was implemented in the state



## Hypothesis Testing on Shall Law

### 1. Analysis of Average Violent Crime rates in Shall law states and states not having Shall law with T-test:

We conduct T-test to know if there is any difference between states having shall law and states that are not having shall law in average violent crime rate.

#### Hypothesis:

Ho: No difference between shall law states and no shall law states

Ha: Significant difference between average violent crime rate in shall law states and average violent crime rate in no shall law states

welch Two sample t-test

```
data: hr$vio by hr$shall
t = 8.2381, df = 613.37, p-value = 1.06e-15
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 122.7622 199.6115
sample estimates:
mean in group 0 mean in group 1
   542.2377      381.0509
```

We can see the p value is  $< 0.05$ , hence null hypothesis is rejected. We conclude that there is significant difference in the violent crime rate between states having shall law and states not having shall law.

### 2. Analysis of Average Murder rates in Shall law states and states not having Shall law with T-test:

We conduct T-test to know if there is any difference between states having shall law and states that are not having shall law in average murder rate.

#### Hypothesis:

Ho: No difference between shall law states and no shall law states

Ha: Significant difference between average murder rate in shall law states and average murder crime rate in no shall law states

welch Two sample t-test

```
data: hr$mur by hr$shall
t = 8.9797, df = 1069.9, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  2.458192 3.832873
sample estimates:
mean in group 0 mean in group 1
   8.429392      5.283860
```

P-value is  $< 0.05$ , hence null hypothesis is rejected. We conclude that there is significant difference in the murder rate between states having shall law and states not having shall law.

### 3. Analysis of Average Robbery rates in Shall law states and states not having Shall law with T-test:

We conduct T-test to know if there is any difference between states having shall law and states that are not having shall law in average robbery rate.

#### Hypothesis:

Ho: No difference between shall law states and no shall law states

Ha: Significant difference between average robbery rate in shall law states and average murder crime rate in no shall law states

```
welch Two sample t-test

data:  hr$rob by hr$shall
t = 10.428, df = 1012.2, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 68.54833 100.32565
sample estimates:
mean in group 0 mean in group 1
 182.3356      97.8986
```

P-value is  $< 0.05$ , hence null hypothesis is rejected. We conclude that there is significant difference in the robbery rates between states having shall law and states not having shall law.

### 4. Analysis of Average Incarceration Rates in Shall law states and states not having Shall law with T-test:

We conduct T-test to know if there is any difference between states having shall law and states that are not having shall law in average incarceration rate.

#### Hypothesis:

Ho: No difference between shall law states and no shall law states

Ha: Significant difference between average incarceration rate in shall law states and average murder crime rate in no shall law states

```
welch Two sample t-test

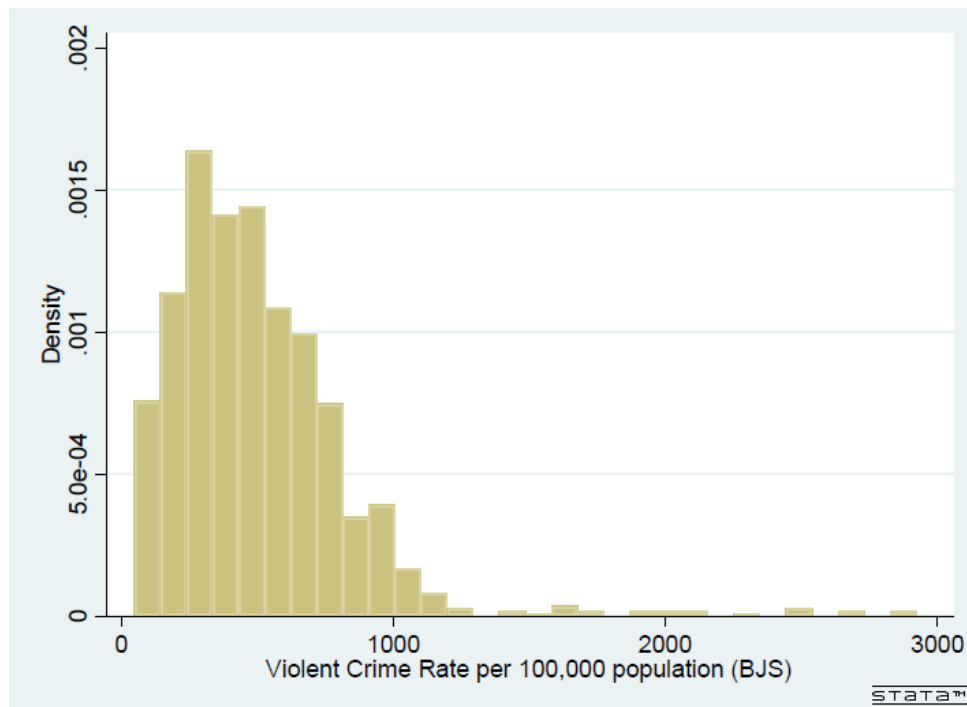
data:  hr$incarc_rate by hr$shall
t = -1.5881, df = 564.91, p-value = 0.1128
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-39.518171  4.183724
sample estimates:
mean in group 0 mean in group 1
 222.2872      239.9544
```

The p-value is **not**  $< 0.05$ , hence null hypothesis is not rejected. There is no significant difference in average incarceration rate between states having shall law and states not having shall law

With a clearer picture and understanding of the data now, we performed regression models and compared how Shall law affects the crime rates. The below sections have various types of regression models and insights from these models. (at the end of the report, we have attached all the .do files written for this project)

## Regression Analysis

To model the violent crime rate over the years we look at the distribution of violent crime rate and we plotted the histogram for the same. As seen in the graph the histogram is highly right skewed and therefore we take the log for the crime rate before modelling the data.



Before we blindly go ahead and run models on the data, our main focus was on finding extent up to which shall law has an impact on the violent crime rate. By the help of a covariance matrix we found variables that are correlated to each other.

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

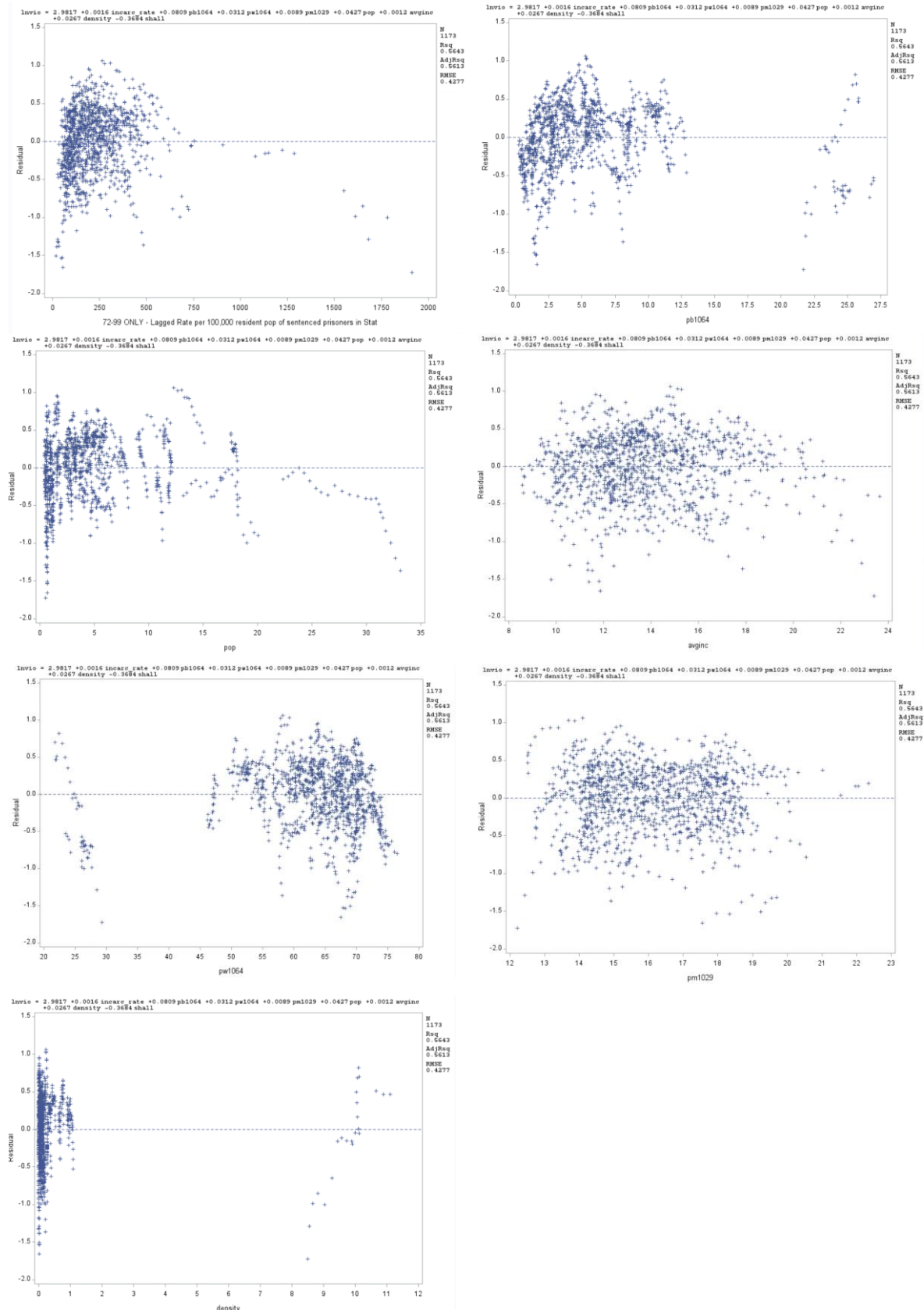
	vio	mur	rob	incarc~e	pb1064	pw1064	pm1029	pop	avginc	density
vio	1.0000									
mur	0.8265	1.0000								
rob	0.9071	0.7976	1.0000							
incarc_rate	0.7027	0.7096	0.5668	1.0000						
pb1064	0.5698	0.6018	0.5812	0.5308	1.0000					
pw1064	-0.5730	-0.6154	-0.5842	-0.5271	-0.9820	1.0000				
pm1029	-0.1696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

From the above matrix we can see that robbery rate is highly correlated to violent crime rate and murder rate is also highly correlated to violent crime rate.

We regressed only violent crime rate against shall law to see the effect of shall law on violent crime rate not considering any other factor playing its part. As expected the model fit of the model was very bad, had an R-square value of 0.08. Shall law was highly significant, and the model interpreted that if the state employed shall law the violent crime rate would decrease by 44.2% when compared to shall law not being implemented. This result is bogus because a lot of other significant variables were residing in the error term & had a clear case of omitted variable bias.

# 1. Pooled OLS Model

Ignoring the panel nature of the data, change in crime rate across different states was checked by using pooled OLS regression. Before running the model, we did check for heteroskedasticity in the data. While the residuals plot didn't give much information w.r.t presence of heteroscedasticity (function of variance was unknown, so WLS didn't in solving for heteroskedasticity), as a safe practice we used cluster robust standard errors under the assumption that heteroskedasticity exists.



Above graphs shows the residual plots of individual variables plotted against residual

```
. reg lnvio incarc_rate pb1064 pw1064 pm1029 pop avginc density shall, vce(cluster state)
```

```
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)

lnvio	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
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
shall	-.3683869	.113937	-3.23	0.002	-.5972361	-.1395378
_cons	2.981738	2.166513	1.38	0.175	-1.369831	7.333307

We observe that the crime rate is decreases by 36.84% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Also, we can observe that if the incarceration rate increases by 1 unit the crime rate also increases by 0.16%. We observed that the impact of shall law on violent crime rate decreased from 44% to 36.8%. population, incarc\_rate and shall law are highly significant variables. The least square estimators are no longer efficient.

Interaction terms where created and tested with the model. These interaction terms were highly insignificant and didn't add value into the model. Thus, they were exempted from the final model which was to be regressed.

The least square estimators are no longer BLUE as they are inefficient. We move ahead with panel effect modelling.

## 2. Fixed Effects Model

Since it is panel data, we perform panel regression. There are 3 ways of doing it – least square dummy variable estimator, fixed effects estimator & random effects estimator. Least square dummy variable estimator is not feasible because we create a dummy variable for every observation, i.e. 1173 dummy variables. So, we go ahead with Fixed Effects estimator.

To check the within effects we perform the Fixed Effects panel regression. We observe that the impact of crime rate on violent crime rate drastically goes down to 4.61% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. The incarceration rate has become an insignificant variable and does not have a very high impact on the crime rate.

The population variables (pm1029, pw1064 & pb1064) have become significant variables. At this point, it looks like Fixed Effects model does a great job in capturing the unobserved heterogeneity which Pooled OLS failed to do so. From the fixed effects model, it can be interpreted that when shall law is in effect, the violent crime rate decreases by 4.61% when compared to shall law not in effect.

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

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

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

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

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

lnvio	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
incarc_rate	-.000071	.0002504	-0.28	0.778	-.0005739	.0004318
pb1064	.1042804	.0326849	3.19	0.002	.0386308	.1699301
pw1064	.0408611	.0134585	3.04	0.004	.0138289	.0678932
pm1029	-.0502725	.0206949	-2.43	0.019	-.0918394	-.0087057
avginc	-.0092037	.0129649	-0.71	0.481	-.0352445	.016837
pop	.0115247	.014224	0.81	0.422	-.0170452	.0400945
density	-.1722901	.1376129	-1.25	0.216	-.4486936	.1041135
shall	-.0461415	.0417616	-1.10	0.275	-.1300223	.0377392
_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)				

### 3. Random Effects Model

To observe both within and between effects we now perform the Random Effects Panel Regression. We observe that the violent crime rate decreases by 6.96% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Population related variables are highly significant. Shall law is significant at 90% confidence interval not at 95%.

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

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

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

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

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

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

To decide which is the better model between Fixed Effects and Random Effects model, we perform the Hausman Test. This test compares the coefficient estimates from the Random Effects model to those from the Fixed Effects model.

```
. quietly xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, fe
. estimates store fe

. quietly xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, re
. estimates store re

. hausman fe re
```

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

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)

According to the Chi Square statistic and the P-value we will have to reject the Null Hypothesis of no endogeneity. We conclude that the Fixed Effects model is a better model for this analysis. From the Hausman test it is established that the Fixed effects model is better than Random Effects model (Random Effects model also risks the occurrence of endogeneity). We go ahead and perform entity fixed effects model and time fixed effects model.

#### 4. Entity Fixed Effects Model

Here in this model, each state has an intercept of its own.

. reg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.stateid										21	-.4255548	.1049019	-4.06	0.000	-.6313824	-.2197272
										22	.3685392	.057251	6.44	0.000	.2562073	.4808711
Source	SS	df	MS	Number of obs = 1,173		23	-1.131981	.1330361	-8.51	0.000	-1.39301	-.8709513				
						24	.3961276	.0592262	6.69	0.000	.2799202	.512335				
Model	459.854887	58	7.92853254	F(SS, 1114) = 306.93		25	.2869058	.1489839	1.93	0.054	-.005415	.5792265				
Residual	28.7766714	1,114	.025831841	Prob > F = 0.0000		26	.2449163	.0991731	2.47	0.014	.0503291	.4395035				
						27	-.5760094	.1251856	-4.60	0.000	-.8216356	-.3303833				
Total	488.631558	1,172	.416921125	R-squared = 0.9411		28	-.392985	.0771168	-5.10	0.000	-.5442955	-.2416745				
						29	.1455349	.0922059	1.58	0.115	-.0353819	.3264516				
						30	-.9910133	.1051692	-9.42	0.000	-1.197365	-.7846612				
lnvio	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	31	-.4432373	.11437	-3.88	0.000	-.6676422	-.2188325				
						32	.3226112	.0865611	3.73	0.000	.15277	.4924524				
incarc_rate	-.000071	.0000936	-0.76	0.448	-.0002547	.0001126	33	-1.277052	.139976	-9.12	0.000	-1.551698	-1.002406			
pb1064	.1042804	.0177564	5.87	0.000	.0694407	.1391201	34	.1222139	.1265728	0.97	0.334	-.126134	.3705618			
pw1064	.0408611	.0050745	8.05	0.000	.0309044	.0508177	35	.3817845	.0768095	4.97	0.000	.2310769	.5324921			
pm1029	-.0502725	.0064037	-7.85	0.000	-.0628373	-.0377078	36	.4354412	.1459921	2.98	0.003	.1489906	.7218917			
avginc	-.0092037	.0059083	-1.56	0.120	-.0207963	.0023889	37	-.0965572	.0549367	-1.76	0.079	-.2043483	.0112339			
pop	.0115247	.0087239	1.32	0.187	-.0055924	.0286417	38	-1.843342	.111446	-16.54	0.000	-2.06201	-1.624675			
density	-.1722901	.0850362	-2.03	0.043	-.3391392	-.0054409	39	-.1884885	.1257346	-1.50	0.134	-.4351919	.0582149			
shall	-.0461415	.0188668	-2.45	0.015	-.08316	-.009123	40	-.0411461	.0684913	-0.60	0.548	-.1755325	.0932403			
stateid							41	.0049471	.1153633	0.04	0.966	-.2214067	.2313009			
2	.0559649	.0727213	0.77	0.442	-.0867213	.198651	42	-.3249639	.1370178	-2.37	0.018	-.593806	-.0561218			
4	.2404116	.0887689	2.71	0.007	.0662385	.4145848	44	-.1003761	.1577365	-0.64	0.525	-.4098703	.209118			
5	-.1272757	.0664795	-1.91	0.056	-.2577149	.0031635	45	.334051	.0576949	5.79	0.000	.2208482	.4472539			
6	.2442405	.2304245	1.06	0.289	-.2078744	.6963554	46	-1.024605	.0989142	-10.36	0.000	-1.218684	-.8305256			
8	-.1050866	.1121747	-0.94	0.349	-.3251842	.1150109	47	.0446805	.0720137	0.62	0.535	-.0966174	.1859784			
9	-.0955651	.1348337	-0.71	0.479	-.3601218	.1689916	48	.0526546	.1451395	0.36	0.717	-.2321229	.3734321			
10	.0975979	.0767356	1.27	0.204	-.0529647	.2481605	49	-.3039108	.1136771	-2.67	0.008	-.526956	-.0808655			
11	2.759405	.7797288	3.54	0.000	1.229502	4.289307	50	-1.254522	.1352965	-9.27	0.000	-1.519987	-.9890373			
12	.6771463	.1135223	5.96	0.000	.4544047	.8998878	51	-.6017665	.0614983	-9.79	0.000	-.7224321	-.4811009			
13	.0225319	.0538476	0.42	0.676	-.0831224	.1281861	53	-.1321725	.1036698	-1.27	0.203	-.3355826	.0712377			
15	-1.127962	.2590434	-4.35	0.000	-1.63623	-.6196937	54	-.9691482	.122316	-7.92	0.000	-1.209144	-.7291524			
16	-.5029989	.1220814	-4.12	0.000	-.7425344	-.2634634	55	-.7812224	.1174512	-6.65	0.000	-1.011673	-.5507718			
17	.4085668	.1072083	3.81	0.000	.1982138	.6189197	56	-.4804004	.121985	-3.94	0.000	-.7197467	-.2410541			
18	-.2056563	.1110607	-1.85	0.064	-.4235679	.0122553										
19	-.62914	.1277561	-4.92	0.000	-.8798097	-.3784703	cons	4.036775	.3893662	10.37	0.000	3.272801	4.800749			
20	-.180834	.1015614	-1.78	0.075	-.3801071	.0184391										

Shall law is significant and indicates a 4.6% drop in violent crime rate when shall law is present.



## 5. Time Fixed Effects Model

In order to observe the Shall law effect on the crime rate over the years we perform Time Fixed Effects Panel Regression.

```
. xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, fe vce(cluster stateid)
```

Fixed-effects (within) regression	Number of obs	=	1,173
Group variable: <b>stateid</b>	Number of groups	=	51
R-sq:	Obs per group:		
within = <b>0.4180</b>	min =		23
between = <b>0.0419</b>	avg =		23.0
overall = <b>0.0009</b>	max =		23
corr(u_i, Xb) = <b>-0.2929</b>	F(30,50)	=	56.86
	Prob > F	=	0.0000
(Std. Err. adjusted for 51 clusters in stateid)			

lnvio	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
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
avginc	.0009587	.0164931	0.06	0.954	-.0321688	.0340861
pop	-.0047544	.0152294	-0.31	0.756	-.0353436	.0258347
density	-.091555	.1238622	-0.74	0.463	-.3403396	.1572296
shall	-.0279935	.0407168	-0.69	0.495	-.1097757	.0537886
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)				

The effect of shall law on violent crime rate further decreases. The violent crime rate decreases by 2.79% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. From 1983-1995 shows a major trend with an increase in the magnitude of the coefficients. And after 1996 we see a drop till 1999.

Furthermore, to check if there is any trend effect we perform a hypothesis test. This hypothesis test checks for the joint significance of time effects

### Hypothesis:

H0: Year78=year79=year80.....=year99=0

H1: Atleast one of the year estimator is not equal to 0





We observe that the murder rate is going down by 6.1% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Shall law is not a significant variable.

```
. xtreg lnmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, fe cluster(stateid)
```

Fixed-effects (within) regression	Number of obs	=	1,173
Group variable: <b>stateid</b>	Number of groups	=	51
R-sq:	Obs per group:		
within = <b>0.2905</b>	min =		23
between = <b>0.1945</b>	avg =		23.0
overall = <b>0.1413</b>	max =		23
	F(30,50)	=	81.49
corr(u_i, Xb) = <b>-0.8336</b>	Prob > F	=	0.0000
(Std. Err. adjusted for 51 clusters in stateid)			

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
incarc_rate	-.0001164	.0003631	-0.32	0.750	-.0008457	.0006129
pb1064	.0219833	.0758151	0.29	0.773	-.1302958	.1742624
pw1064	-.0004893	.0201044	-0.02	0.981	-.0408701	.0398915
pm1029	.0691941	.0417945	1.66	0.104	-.0147526	.1531408
avginc	.0566492	.0165554	3.42	0.001	.0233967	.0899017
pop	-.0320769	.0209819	-1.53	0.133	-.0742202	.0100664
density	-.5442635	.3192203	-1.70	0.094	-1.185436	.0969093
shall	-.0149524	.0382403	-0.39	0.697	-.0917603	.0618556
year						
78	-.0007195	.0322722	-0.02	0.982	-.0655401	.0641011
79	.0592481	.0311141	1.90	0.063	-.0032465	.1217427
80	.0901814	.041058	2.20	0.033	.0077139	.1726489
81	.1021543	.0510636	2.00	0.051	-.00041	.2047186
82	.0224098	.0581861	0.39	0.702	-.0944604	.1392799
83	-.0314385	.0640621	-0.49	0.626	-.1601111	.0972341
84	-.1359192	.071662	-1.90	0.064	-.2798565	.0080181
85	-.0866144	.0856965	-1.01	0.317	-.2587409	.0855122
86	-.0122752	.0927286	-0.13	0.895	-.1985262	.1739758
87	-.0290338	.0999408	-0.29	0.773	-.2297707	.1717032
88	-.0174594	.1196893	-0.15	0.885	-.2578626	.2229437
89	-.0145617	.1321034	-0.11	0.913	-.2798993	.2507759
90	.059998	.1649718	0.36	0.718	-.2713577	.3913537
91	.1053071	.1754909	0.60	0.551	-.2471767	.4577909
92	.0681002	.1828352	0.37	0.711	-.2991352	.4353355
93	.1544297	.1898113	0.81	0.420	-.2268176	.535677
94	.0442648	.1971908	0.22	0.823	-.3518047	.4403342
95	.0556601	.1989082	0.28	0.781	-.3438588	.455179
96	-.015709	.2125365	-0.07	0.941	-.4426011	.4111831
97	-.1221824	.2186706	-0.56	0.579	-.5613952	.3170304
98	-.1863381	.2332966	-0.80	0.428	-.6549281	.2822519
99	-.2554286	.2420434	-1.06	0.296	-.741587	.2307298
_cons	.1882653	1.056771	0.18	0.859	-1.934322	2.310853
sigma_u	1.1362086					
sigma_e	.20281999					
rho	.96911961	(fraction of variance due to u_i)				

From the time fixed effects model, we can see that the model has improved. The murder rate is decreases by 1.4% now for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Shall law is not a significant variable.

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

Fixed-effects (within) regression	Number of obs	=	1,173
Group variable: <b>stateid</b>	Number of groups	=	51
R-sq:	Obs per group:		
within = <b>0.0366</b>	min =		23
between = <b>0.0531</b>	avg =		23.0
overall = <b>0.0521</b>	max =		23
	F(8,50)	=	2.86
corr(u_i, Xb) = <b>-0.0859</b>	Prob > F	=	0.0108
(Std. Err. adjusted for 51 clusters in stateid)			

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
incarc_rate	-.0000763	.000321	-0.24	0.813	-.0007211	.0005685
pb1064	.1115421	.0511546	2.18	0.034	.008795	.2142891
pw1064	.0271807	.0164344	1.65	0.104	-.0058286	.0601901
pm1029	.0111817	.0290976	0.38	0.702	-.0472626	.069626
avginc	-.0175195	.0220352	-0.80	0.430	-.0617784	.0267395
pop	.0163332	.0275874	0.59	0.556	-.0390778	.0717441
density	-.1860917	.1663413	-1.12	0.269	-.520198	.1480147
shall	-.0078189	.0551653	-0.14	0.888	-.1186217	.1029838
_cons	2.445723	1.012584	2.42	0.019	.4118887	4.479557
sigma_u	.9174441					
sigma_e	.21514885					
rho	.94787229	(fraction of variance due to u_i)				

Also, the robbery rate is going down by 0.78% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Shall law is not a significant variable.

```
. xtreg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, fe cluster(stateid)
```

Fixed-effects (within) regression	Number of obs	=	1,173
Group variable: <b>stateid</b>	Number of groups	=	51
R-sq:	Obs per group:		
within = 0.2359	min =		23
between = 0.1358	avg =		23.0
overall = 0.1362	max =		23
	F(30,50)	=	40.77
corr(u_i, Xb) = 0.1441	Prob > F	=	0.0000
(Std. Err. adjusted for 51 clusters in stateid)			

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
lnrob					
incarc_rate	.0000314	.0003477	0.09	0.928	-.000667 .0007297
pb1064	.0141078	.0840609	0.17	0.867	-.1547335 .1829491
pw1064	-.0128322	.0327626	-0.39	0.697	-.0786379 .0529734
pm1029	.1046049	.072997	1.43	0.158	-.0420138 .2512236
avginc	.0143569	.0247676	0.58	0.565	-.0353903 .064104
pop	.0000164	.0259374	0.00	0.999	-.0520805 .0521133
density	-.0447449	.1982135	-0.23	0.822	-.4428684 .3533786
shall	.0268298	.0521753	0.51	0.609	-.0779673 .1316269
year					
78	.0328497	.0216897	1.51	0.136	-.0107154 .0764148
79	.1375917	.032117	4.28	0.000	.0730828 .2021006
80	.243408	.045464	5.35	0.000	.1520908 .3347251
81	.2737088	.0508793	5.38	0.000	.1715147 .375903
82	.21599	.0644109	3.35	0.002	.0866168 .3453632
83	.1208158	.0867066	1.39	0.170	-.0533395 .2949711
84	.078831	.1064308	0.74	0.462	-.1349416 .2926036
85	.1131495	.1272629	0.89	0.378	-.1424655 .3687645
86	.1895678	.1521449	1.25	0.219	-.1160242 .4951598
87	.1572151	.1688872	0.93	0.356	-.1820049 .496435
88	.1927596	.1878849	1.03	0.310	-.1846184 .5701376
89	.2487313	.2140573	1.16	0.251	-.1812154 .6786781
90	.3509806	.2668617	1.32	0.194	-.185027 .8869881
91	.4668537	.2791767	1.67	0.101	-.0938891 1.027596
92	.4633221	.2951262	1.57	0.123	-.1294562 1.0561
93	.4796983	.3082342	1.56	0.126	-.1394084 1.098805
94	.4943754	.3234124	1.53	0.133	-.1552175 1.143968
95	.4940171	.3338462	1.48	0.145	-.1765328 1.164567
96	.4341625	.3504351	1.24	0.221	-.2697072 1.138032
97	.3652393	.3581743	1.02	0.313	-.354175 1.084654
98	.2677144	.3690383	0.73	0.472	-.4735208 1.00895
99	.1894683	.3845414	0.49	0.624	-.5829059 .9618425
_cons	3.27912	1.676644	1.96	0.056	-.088518 6.646759
sigma_u	.88484023				
sigma_e	.19352746				
rho	.95434775	(fraction of variance due to u_i)			

The robbery rate now decreases by 2.6% for those states who have the shall law implemented as compared to the other states where the shall law is not implemented. Shall law is not a significant variable. For both murder & robbery rate, time effects is significant.

## 7. Non – Linear Regression in Fixed Effects Model

```
Call:
plm(formula = vio ~ incarc_rate + incarc_sq + pb1064 + pw1064 +
      pm1029 + pm1029sq + pop + avginc + avgincsq + density + shall,
      data = data2, index = c("stateid", "year"), method = "within")

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

Residuals:
    Min.    1st Qu.    Median    3rd Qu.    Max.
-707.0787 -46.2730  -3.2072  45.0785  795.3026

Coefficients:
            Estimate Std. Error t-value Pr(>|t|)
incarc_rate  2.0549e-01  9.1159e-02  2.2542  0.024380 *
incarc_sq   -6.4995e-05  6.7489e-05 -0.9630  0.335733
pb1064       1.0067e+01  1.1382e+01  0.8845  0.376635
pw1064       1.9847e+00  3.3996e+00  0.5838  0.559477
pm1029       5.5114e+01  3.7273e+01  1.4786  0.139519
pm1029sq    -1.9934e+00  1.0967e+00 -1.8177  0.069387 .
pop          8.6504e+00  5.2552e+00  1.6461  0.100032
avginc       9.8069e+01  1.6465e+01  5.9561  3.463e-09 ***
avgincsq    -3.1518e+00  5.3066e-01 -5.9395  3.820e-09 ***
density     -3.0984e+02  7.0666e+01 -4.3846  1.272e-05 ***
shall       -3.2899e+01  1.1578e+01 -2.8416  0.004571 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 13576000
Residual Sum of Squares: 10308000
R-Squared: 0.24073
Adj. R-Squared: 0.19904
F-statistic: 32.0225 on 11 and 1111 DF, p-value: < 2.22e-16
```

In the above model we have added `incarc_sq` (square term of the variable “`incarc_rate`”, incarceration rate), `pm1029sq` (square term of the variable “`pm1029`”, male population percentage), and `avgincsq` (square term of the variable “`avginc`”, average income). Adding non-linear terms has made the variable “`shall`” significant in the model but made the male population percentage and white people population percentage insignificant. This model doesn’t seem to improve the model when compared to the model without non-linear terms.

## Conclusion

After running a series of regression models, we have got a much better picture on the effect of shall law on crime rate. From our best model we saw that implementation of shall law reduces the crime rate by just 2.7% and is insignificant. This value is pretty low from a world point of view.

**The above achieved result tells us that there is no significant impact of shall law on crime rate.**

## Limitations

There might be few cases which is preventing us from thoroughly validating our model. 3 main cases are –

1. Heteroskedasticity: Apart from the investigation performed on the data for identifying heteroskedasticity, a clear culprit variable couldn’t be identified. The graphs didn’t depict much and also no knowledge about the function of variance hampered from employing Weighted Least Squares. To mitigate the risk of heteroskedasticity affecting our models, precaution was taken by using robust cluster standard errors.
2. Omitted variable bias: There might have been few variables which might not have been provided for analysis. These omitted variables could explain the effect the shall law on violent crime rate to a better extent. Due to this there could be omitted variable bias which can affect our models. Few omitted variables could be policies that vary between states and over time which help in governing the shall laws.
3. Simultaneous Causality: We sensed the presence of simultaneous causality bias in the data. Let’s look into it – violent crime rate/ incarceration rate. This can be looked in two ways. If the incarceration rate at a place is high i.e. more number of law offenders are getting prisoned, then this instills a fear in the public and would in turn reduce the crime rate in that particular area. Another way of looking at this is, if the crime rate of a place is exceedingly high then the law enforces (police/ government) would deploy more squad of police and tighten the security. By doing so the incarceration would also increase. Another case of simultaneous causality could be between crime rate and shall law. If the crime rates at a particular state has always been low, then there wouldn’t be a need to implement a concealed weapon law to reduce the crime. Also, if there is a high crime rate at a state over a long period of time, this would force the policy makers to introduce shall law in that state.

\* from this page onwards, the report contains all the code which was written for this project\*

----- BEGIN OF ALL DO FILES -----

\*\*\*R Code\*\*\*

```
library(readstata13)
library(ggplot2)
library(dplyr)
library(directlabels)
data1<-read.dta13("guns.dta")
data2<- data1

# plots
attach(data2)
s<- ggplot(data = data2,aes(y=vio))

# Scatter plots

s+ geom_point(aes(x=avginc)) +geom_smooth(aes(x=avginc),method="lm", se=F)+
  labs(title="Violent crime rate Vs Average Income",
    y="Violence Rate",
    x="Average Income(in k)")

s+ geom_point(aes(x=incarc_rate)) +geom_smooth(aes(x=incarc_rate),method="lm", se=F)+
  labs(title="Incarceration Rate Vs Violent crime rate",
    y="Violence Rate",
    x="Incarceration Rate(previous year)")

s+ geom_point(aes(x=density)) +geom_smooth(aes(x=density),method="lm", se=F)+
  labs(title="Population Density Vs Violence Rate",
    y="Violence Rate",
    x="Population Density(per sq.mile / 1000)")

s+ geom_point(aes(x=pop)) +geom_smooth(aes(x=pop),method="lm", se=F)+
  labs(title="Population Vs Violence Rate",
    y="Violence Rate",
    x="Population (in millions)")

s+ geom_point(aes(x=pm1029)) +geom_smooth(aes(x=pm1029),method="lm", se=F)+
  labs(title="Male Population percentage Vs Violence Rate",
    y="Violence Rate",
    x="Male Population percentage (btwn age 10-29)")

s+ geom_point(aes(x=pw1064)) +geom_smooth(aes(x=pw1064),method="lm", se=F)+
  labs(title="White Population percentage Vs Violence Rate",
    y="Violence Rate",
    x="White Population percentage (btwn age 10-64)")

s+ geom_point(aes(x=pb1064)) +geom_smooth(aes(x=pb1064),method="lm", se=F)+
  labs(title="Black Population percentage Vs Violence Rate",
    y="Violence Rate",
    x="Black Population percentage (btwn age 10-64)")

# State wise plots

shall0=filter(data2, shall == 0)
shall1=filter(data2, shall == 1)
p0<-ggplot(data=shall0)
p1<-ggplot(data=shall1)
p0+geom_line(aes(x=year,y=vio,group = stateid,color=stateid))+
  geom_dl(aes(label = stateid,x=year,y=vio,group = stateid,color=stateid), method = list(dl.combine("first.points",
"last.points"), cex = 0.8))+
  labs(title="State wise violent crime Rate when Shall-carry law isn't in effect",
    y="Violence Rate")
p1+geom_line(aes(x=year,y=vio,group = stateid,color=stateid))+
  geom_dl(aes(label = stateid,x=year,y=vio,group = stateid,color=stateid), method = list(dl.combine("first.points",
"last.points"), cex = 0.8))+
  labs(title="State wise violent crime Rate when Shall-carry law is in effect",
    y="Violence Rate")

# Non-Linear Fixel Effect Model
data2$incarc_sq <- data2$incarc_rate*data2$incarc_rate
```

```
data2$pm1029sq <- data2$pm1029 * data2$pm1029
data2$avgincsq <- data2$avginc * data2$avginc
nl_model <- plm(vio ~ incarc_rate + incarc_sq + pb1064 + pw1064 + pm1029 + pm1029sq + pop + avginc + avgincsq +
density + shall,data = data2,method = 'within',index = c("stateid","year"))
summary(nl_model)
```

```
install.packages('ggplot2')
library(ggplot2)
library(dplyr)
library(tidyr)
library(haven)
```

```
setwd("C:/Users/BHARGAV/Desktop/Econometrics/project/project")
hr <- read_dta('guns.dta')
hr$rob
summary(hr)
```

```
p <- ggplot(aes(x=vio),data = hr)+
  geom_histogram(color="black", fill="gray20", bins=30)+
  labs(title="crime rate for 'shall law' and 'no shall law'", x="crime rate", y="frequency")
p1 = p + facet_wrap(~shall)
p1
```

```
by(hr$vio, hr$shall, summary)
by(hr$mur, hr$shall, summary)
by(hr$rob, hr$shall, summary)
```

```
t.test(hr$vio~hr$shall)
t.test(hr$mur~hr$shall)
t.test(hr$rob~hr$shall)
```

```
by(hr$vio, hr$stateid, summary)
summary(hr$incarc_rate)
by(hr$incarc_rate, hr$shall, summary)
t.test(hr$incarc_rate~hr$shall)
```

### \*\*\*STATA DO FILE WITH OUTPUTS\*\*\*

```
use "H:\econ\project\guns.dta", clear
des
summ
histogram vio
```

```
use guns.dta
describe
```

```
/* create log variable for vio */
gen lnvio = log(vio)
```

```
/* correlation matrix */
corr vio mur rob incarc_rate pb1064 pw1064 pm1029 pop avginc density
/* (obs=1,173)
```

```

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

From the matrix we can see that mur & rob are highly correlated to vio variable. We'll have to skip these variables while performing regression. \*/

```
/* let us check how only the shall law has an impact on vio rate */
```

```

reg lnvio 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
-----

```

We can see that, when shall law is implemented in a state, the violence rate drops by 44.2% \*/

/\* since we are employing regression on panel data, it is advised to use robust standard errors \*/

```
reg lnvio shall, vce(robust)
```

```

/*
Linear regression
Number of obs = 1,173
F(1, 1171) = 86.86
Prob>F = 0.0000
R-squared = 0.0866
Root MSE = .61735

```

```

-----
|      Robust
lnvio |   Coef.   Std. Err.      t    P>|t|   [95% Conf. Interval]
-----+-----
shall | -.4429646   .0475283   -9.32  0.000   -.5362148   -.3497144
_cons |  6.134919   .0193039   317.81  0.000    6.097045   6.172793
-----

```

We can observe changes in the t-values & standard errors but coefficients remain same. \*/

/\* let us go ahead and regress a pooled OLS model with robust standard errors \*/

Adding the interaction term doesn't improve the fit of the model. Hence we'll go ahead the model without the interaction term \*/

/\* Since it is panel data the least square estimators are not efficient. This is due to the fact that there can be unobserved heterogeneity.

We'll go ahead and create a fixed effect model & interpret the fixed effect estimators. We can do this in two ways - dummy variable creation or

fixed effect estimator. since N is large it isn't feasible to do so. Let's go ahead with fixed effect estimator.

We have to let Stata know that we are dealing with panel data -\*/

```
xtset stateid year
```

```
/* panel variable: stateid (strongly balanced)
```

```
time variable: year, 77 to 99
```

```
delta: 1 unit */
```

/\* since it is a balanced panel data, it makes sense to use fixed effect over random effects \*/

```
xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, 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

```

```

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

```

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

```

-----
|      Robust
lnvio |   Coef.   Std. Err.      t    P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.000071   .0002504   -0.28  0.778   -.0005739   .0004318
pb1064 | .1042804   .0326849    3.19  0.002   .0386308   .1699301

```

```

pw1064 | .0408611 .0134585 3.04 0.004 .0138289 .0678932
pm1029 | -.0502725 .0206949 -2.43 0.019 -.0918394 -.0087057
avginc | -.0092037 .0129649 -0.71 0.481 -.0352445 .016837
pop | .0115247 .014224 0.81 0.422 -.0170452 .0400945
density | -.1722901 .1376129 -1.25 0.216 -.4486936 .1041135
shall | -.0461415 .0417616 -1.10 0.275 -.1300223 .0377392
_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)
-----+----- */
/* we can have 2 more variations for fixed effects. entity fixed & time fixed effects. We'll good ahead with both */
/* fixed entity fixed effect. create dummy variable for state */
reg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.stateid
/*
Source |      SS      df    MS  Number of obs = 1,173
-----+----- F(58, 1114) = 306.93
Model | 459.854887    58 7.92853254 Prob > F = 0.0000
Residual | 28.7766714  1,114 .025831841 R-squared = 0.9411
-----+----- Adj R-squared = 0.9380
Total | 488.631558  1,172 .416921125 Root MSE = .16072

-----+-----
lnvio |   Coef.   Std. Err.    t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.000071 .0000936  -0.76  0.448  -.0002547 .0001126
pb1064 | .1042804 .0177564   5.87  0.000   .0694407 .1391201
pw1064 | .0408611 .0050745   8.05  0.000   .0309044 .0508177
pm1029 | -.0502725 .0064037  -7.85  0.000  -.0628373 -.0377078
avginc | -.0092037 .0059083  -1.56  0.120  -.0207963 .0023889
pop | .0115247 .0087239   1.32  0.187  -.0055924 .0286417
density | -.1722901 .0850362  -2.03  0.043  -.3391392 -.0054409
shall | -.0461415 .0188668  -2.45  0.015  -.08316 -.009123
|
stateid |
2 | .0559649 .0727213   0.77  0.442  -.0867213 .198651
4 | .2404116 .0887689   2.71  0.007   .0662385 .4145848
5 | -.1272757 .0664795  -1.91  0.056  -.2577149 .0031635
6 | .2442405 .2304245   1.06  0.289  -.2078744 .6963554
8 | -.1050866 .1121747  -0.94  0.349  -.3251842 .1150109
9 | -.0955651 .1348337  -0.71  0.479  -.3601218 .1689916
10 | .0975979 .0767356   1.27  0.204  -.0529647 .2481605
11 | 2.759405 .7797288   3.54  0.000   1.229502 4.289307
12 | .6771463 .1135223   5.96  0.000   .4544047 .8998878
13 | .0225319 .0538476   0.42  0.676  -.0831224 .1281861
15 | -1.127962 .2590434  -4.35  0.000  -1.63623 -.6196937
16 | -.5029989 .1220814  -4.12  0.000  -.7425344 -.2634634
17 | .4085668 .1072083   3.81  0.000   .1982138 .6189197
18 | -.2056563 .1110607  -1.85  0.064  -.4235679 .0122553
19 | -.62914 .1277561  -4.92  0.000  -.8798097 -.3784703
20 | -.180834 .1015614  -1.78  0.075  -.3801071 .0184391
21 | -.4255548 .1049019  -4.06  0.000  -.6313824 -.2197272
22 | .3685392 .057251   6.44  0.000   .2562073 .4808711
23 | -1.131981 .1330361  -8.51  0.000  -1.39301 -.8709513
24 | .3961276 .0592262   6.69  0.000   .2799202 .512335
25 | .2869058 .1489839   1.93  0.054  -.005415 .5792265
26 | .2449163 .0991731   2.47  0.014   .0503291 .4395035
27 | -.5760094 .1251856  -4.60  0.000  -.8216356 -.3303833
28 | -.392985 .0771168  -5.10  0.000  -.5442955 -.2416745
29 | .1455349 .0922059   1.58  0.115  -.0353819 .3264516
30 | -.9910133 .1051692  -9.42  0.000  -1.197365 -.7846612
31 | -.4432373 .11437  -3.88  0.000  -.6676422 -.2188325
32 | .3226112 .0865611   3.73  0.000   .15277 .4924524
33 | -1.277052 .139976  -9.12  0.000  -1.551698 -1.002406
34 | .1222139 .1265728   0.97  0.334  -.126134 .3705618
35 | .3817845 .0768095   4.97  0.000   .2310769 .5324921
36 | .4354412 .1459921   2.98  0.003   .1489906 .7218917
37 | -.0965572 .0549367  -1.76  0.079  -.2043483 .0112339
38 | -1.843342 .111446  -16.54  0.000  -2.06201 -1.624675

```



```

39 | -.1884885 .1257346 -1.50 0.134 -.4351919 .0582149
40 | -.0411461 .0684913 -0.60 0.548 -.1755325 .0932403
41 | .0049471 .1153633 0.04 0.966 -.2214067 .2313009
42 | -.3249639 .1370178 -2.37 0.018 -.593806 -.0561218
44 | -.1003761 .1577365 -0.64 0.525 -.4098703 .209118
45 | .334051 .0576949 5.79 0.000 .2208482 .4472539
46 | -1.024605 .0989142 -10.36 0.000 -1.218684 -.8305256
47 | .0446805 .0720137 0.62 0.535 -.0966174 .1859784
48 | .0526546 .1451395 0.36 0.717 -.2321229 .3374321
49 | -.3039108 .1136771 -2.67 0.008 -.526956 -.0808655
50 | -1.254522 .1352965 -9.27 0.000 -1.519987 -.9890573
51 | -.6017665 .0614983 -9.79 0.000 -.7224321 -.4811009
53 | -.1321725 .1036698 -1.27 0.203 -.3355826 .0712377
54 | -.9691482 .122316 -7.92 0.000 -1.209144 -.7291524
55 | -.7812224 .1174512 -6.65 0.000 -1.011673 -.5507718
56 | -.4804004 .121985 -3.94 0.000 -.7197467 -.2410541
|
_cons | 4.036775 .3893662 10.37 0.000 3.272801 4.800749
-----*/

/* the estimate on shall law hasnt changed. let's go with time-fixed effect */
xtreg Invio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, 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 = 0.4180                    min =      23
    between = 0.0419                   avg =     23.0
    overall = 0.0009                   max =      23

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

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

-----+-----
|               Robust
Invio |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
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
avginc | .0009587 .0164931   0.06  0.954   -.0321688 .0340861
pop | -.0047544 .0152294  -0.31  0.756   -.0353436 .0258347
density | -.091555 .1238622  -0.74  0.463   -.3403396 .1572296
shall | -.0279935 .0407168  -0.69  0.495   -.1097757 .0537886
|
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)
-----+-----

we can see that effect of shall law has decreased more. this model can be better because it explained for a lot of
unobserved characteristics */

/* we can check if the years are jointly significant or not
H0: effects of all time effects = 0
H1: effect not equal to 0 at least for 1 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) = 21.62
Prob > F = 0.0000 */
/* Yes, the time effects are jointly statistically significant */
/* Also, the effect on shall law drops even more. so, this model can be utilized to explain about the data. hence, we prefer a
model with both entity & time effect*/

/* random effects model */
xtreg Invio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, re cluster(stateid)
/*
Random-effects GLS regression           Number of obs   =   1,173
Group variable: stateid                 Number of groups  =    51

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

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

(Std. Err. adjusted for 51 clusters in stateid)
-----+-----
      |           Robust
Invio |   Coef.   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
incarc_rate | .0001888 .0001877    1.01  0.314   -.0001791   .0005567
pb1064 | .1067022 .0270973    3.94  0.000   .0535924   .1598119
pw1064 | .0400716 .0127282    3.15  0.002   .0151248   .0650184
pm1029 | -.0375292 .0180436   -2.08  0.038   -.072894   -.0021643
avginc | -.0105112 .0117802   -0.89  0.372   -.0335999   .0125775

```

```

pop | .0225755 .0116369 1.94 0.052 -.0002323 .0453833
density | .0661588 .0437925 1.51 0.131 -.0196729 .1519905
shall | -.069609 .038845 -1.79 0.073 -.1457438 .0065258
_cons | 3.525463 .7786851 4.53 0.000 1.999268 5.051658
-----+-----
sigma_u | .33790775
sigma_e | .16072287
rho | .81550462 (fraction of variance due to u_i)
-----+----- */

/* test for endogeneity - Hausman test */
quietly xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, fe
estimates store fe
quietly xtreg lnvio incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, re
estimates store re
hausman fe re

/*

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

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) */

/* reject null and conclude at least 1 has endogeneity. from the differences we can suspect density is an endogenous
variable */

/* ----- END of vio variable ----- */
/* ----- BEGIN of rob variable ----- */
use guns.dta
describe

/* create log variable for mur */
gen lnrob = log(rob)

/* let us check how only the shall_law has an impact on mur rate */
reg lnrob shall
/*

Source | SS df MS Number of obs = 1,173
-----+----- F(1, 1171) = 160.90
Model | 129.02655 1 129.02655 Prob>F = 0.0000
Residual | 939.006572 1,171 .801884349 R-squared = 0.1208
-----+----- Adj R-squared = 0.1201
Total | 1068.03312 1,172 .91129106 Root MSE = .89548

lnrob | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
shall | -.7733207 .0609644 -12.68 0.000 -.8929323 -.6537091
_cons | 4.873051 .0300503 162.16 0.000 4.814093 4.93201
-----+-----

```

We can see that, when shall law is implemented in a state, the violence rate drops by 77.3% \*/

```
/* since we are employing regression on panel data, it is advised to use robust standard errors */
reg lnrob shall, vce(robust)
/*
```

```
Linear regression               Number of obs   =   1,173
                               F(1, 1171)      =   124.66
                               Prob > F         =   0.0000
                               R-squared         =   0.1208
                               Root MSE       =   .89548
```

```
-----+-----
      |           Robust
lnrob |   Coef. Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
shall | -.7733207 .0692623 -11.17 0.000   -.9092128   -.6374286
_cons |  4.873051 .0279093  174.60 0.000    4.818293   4.927809
-----+-----
```

We can observe changes in the t-values & standard errors but coefficients remain same. \*/

```
/* let us go ahead and regress a pooled OLS model with robust standard errors
From the above model, we have to remove mur rob variables since they are highly correlated to vio, remodelling - */
reg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, vce(robust)
/*
```

```
Linear regression               Number of obs   =   1,173
                               F(8, 1164)      =   144.90
                               Prob > F         =   0.0000
                               R-squared         =   0.5962
                               Root MSE       =   .60869
```

```
-----+-----
      |           Robust
lnrob |   Coef. Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | .0010057 .0001869   5.38 0.000   .0006391   .0013724
pb1064 | .1021881 .0265948   3.84 0.000   .0500091   .1543672
pw1064 | .0275209 .0135419   2.03 0.042   .0009515   .0540902
pm1029 | .0272565 .0149995   1.82 0.069  -.0021726   .0566856
avginc | .0407325 .0092722   4.39 0.000   .0225404   .0589246
pop | .0778176 .0054853  14.19 0.000   .0670554   .0885799
density | .0905048 .0153545   5.89 0.000   .0603792   .1206303
shall | -.5288202 .0510021 -10.37 0.000  -.6288865  -.4287539
_cons | .9041383 .8893029   1.02 0.310  -.8406777   2.648954
-----+-----
```

we can see that contribution of shall law towards vio rate has decreased. Now vio rate is reduced by 31% when a shall law was introduced. \*/

/\* Since it is panel data the least square estimators are not efficient. This is due to the fact that there can be unobserved heterogeneity.

We'll go ahead and create a fixed effect model & interpret the fixed effect estimators. We can do this in two ways - dummy variable creation or

fixed effect estimator. since N is large it isn't feasible to do so. Let's go ahead with fixed effect estimator.

We have to let Stata know that we are dealing with panel data -\*/

```
xtset stateid year
```

```
/* panel variable: stateid (strongly balanced)
```

```
time variable: year, 77 to 99
```

```
delta: 1 unit */
```

```
/* since it is a balanced panel data, it makes sense to use fixed effect over random effects */
```

```
xtreg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, fe
```

```
/*Fixed-effects (within) regression
```

```
Number of obs   =   1,173
```

```
Group variable: stateid
```

```
Number of groups =    51
```

```
R-sq:
```

```
Obs per group:
```

```
within = 0.0366
```

```
min =    23
```

```
between = 0.0531
```

```
avg =   23.0
```

```
overall = 0.0521
```

```
max =    23
```

$F(8,1114) = 5.29$   
 $\text{corr}(u_i, Xb) = -0.0859$        $\text{Prob} > F = 0.0000$

```

-----
Inrob |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.0000763   .0001253  -0.61  0.542   -.0003222   .0001695
pb1064 | .1115421   .0237693   4.69  0.000   .0649045   .1581796
pw1064 | .0271807   .0067929   4.00  0.000   .0138525   .040509
pm1029 | .0111817   .0085722   1.30  0.192   -.0056378   .0280012
avginc | -.0175195   .007909   -2.22  0.027   -.0330377   -.0020012
pop | .0163332   .0116781   1.40  0.162   -.0065803   .0392466
density | -.1860917   .1138322  -1.63  0.102   -.4094413   .037258
shall | -.0078189   .0252557  -0.31  0.757   -.0573731   .0417352
_cons | 2.445723   .5150678   4.75  0.000   1.435111   3.456335
-----+-----
sigma_u | .9174441
sigma_e | .21514885
rho | .94787229 (fraction of variance due to u_i)
-----

```

*F test that all u\_i=0: F(50, 1114) = 164.06      Prob > F = 0.0000*  
*We can see that the coefficient of shall rate has reduced considerably. If there is unobserved heterogeneity, we can make our model robust to these effects as well - \*/*  
*xtreg Inrob incarc\_rate pb1064 pw1064 pm1029 avginc pop density shall, 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 = 0.0366      min = 23*  
*between = 0.0531      avg = 23.0*  
*overall = 0.0521      max = 23*

$F(8,50) = 2.86$   
 $\text{corr}(u_i, Xb) = -0.0859$        $\text{Prob} > F = 0.0108$

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

```

-----
|           Robust
Inrob |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.0000763   .000321  -0.24  0.813   -.0007211   .0005685
pb1064 | .1115421   .0511546   2.18  0.034   .008795   .2142891
pw1064 | .0271807   .0164344   1.65  0.104   -.0058286   .0601901
pm1029 | .0111817   .0290976   0.38  0.702   -.0472626   .069626
avginc | -.0175195   .0220352  -0.80  0.430   -.0617784   .0267395
pop | .0163332   .0275874   0.59  0.556   -.0390778   .0717441
density | -.1860917   .1663413  -1.12  0.269   -.520198   .1480147
shall | -.0078189   .0551653  -0.14  0.888   -.1186217   .1029838
_cons | 2.445723   1.012584   2.42  0.019   .4118887   4.479557
-----+-----
sigma_u | .9174441
sigma_e | .21514885
rho | .94787229 (fraction of variance due to u_i)
-----

```

*/\* we can have 2 more variations for fixed effects. entity fixed & time fixed effects. We'll good ahead with both \*/*  
*/\* fixed entity fixed effect. create dummy variable for state \*/*  
*reg Inrob incarc\_rate pb1064 pw1064 pm1029 avginc pop density shall i.stateid*  
*/\* Source |      SS      df      MS      Number of obs = 1,173*  
*-----+-----      F(58, 1114) = 378.61*  
*Model | 1016.46714      58 17.5252956      Prob > F = 0.0000*  
*Residual | 51.5659789      1,114 .04628903      R-squared = 0.9517*  
*-----+-----      Adj R-squared = 0.9492*  
*Total | 1068.03312      1,172 .91129106      Root MSE = .21515*

```

-----
Inrob |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.0000763   .0001253  -0.61  0.542   -.0003222   .0001695
pb1064 | .1115421   .0237693   4.69  0.000   .0649045   .1581796

```

```

pw1064 | .0271807 .0067929 4.00 0.000 .0138525 .040509
pm1029 | .0111817 .0085722 1.30 0.192 -.0056378 .0280012
avginc | -.0175195 .007909 -2.22 0.027 -.0330377 -.0020012
pop | .0163332 .0116781 1.40 0.162 -.0065803 .0392466
density | -.1860917 .1138322 -1.63 0.102 -.4094413 .037258
shall | -.0078189 .0252557 -0.31 0.757 -.0573731 .0417352

```

```

|
stateid |
2 | -.2524599 .0973471 -2.59 0.010 -.4434642 -.0614555
4 | .4998573 .118829 4.21 0.000 .2667034 .7330112
5 | -.0886909 .0889917 -1.00 0.319 -.263301 .0859193
6 | .6758399 .3084537 2.19 0.029 .0706242 1.281056
8 | .1977714 .1501607 1.32 0.188 -.0968584 .4924011
9 | .8646919 .1804928 4.79 0.000 .5105477 1.218836
10 | .3987445 .1027208 3.88 0.000 .1971965 .6002924
11 | 3.271549 1.04377 3.13 0.002 1.223571 5.319526
12 | 1.103328 .1519646 7.26 0.000 .8051586 1.401497
13 | .3174942 .0720822 4.40 0.000 .176062 .4589264
15 | -1.003273 .3467639 -2.89 0.004 -1.683657 -.3228892
16 | -1.1913 .1634222 -7.29 0.000 -1.51195 -.8706501
17 | 1.026567 .1435125 7.15 0.000 .7449816 1.308152
18 | .1770861 .1486694 1.19 0.234 -.1146175 .4687897
19 | -.5782475 .1710185 -3.38 0.001 -.9138022 -.2426929
20 | .1063569 .1359533 0.78 0.434 -.1603965 .3731104
21 | -.1137133 .1404251 -0.81 0.418 -.3892408 .1618142
22 | .4261722 .076638 5.56 0.000 .2758012 .5765433
23 | -1.121693 .1780864 -6.30 0.000 -1.471115 -.7722701
24 | .9937587 .0792821 12.53 0.000 .8381997 1.149318
25 | .7654727 .1994347 3.84 0.000 .3741627 1.156783
26 | .7157619 .1327564 5.39 0.000 .4552811 .9762426
27 | .1243381 .1675775 0.74 0.458 -.2044651 .4531412
28 | -.5037359 .103231 -4.88 0.000 -.706285 -.3011868
29 | .6637821 .1234298 5.38 0.000 .421601 .9059632
30 | -1.19872 .1407829 -8.51 0.000 -1.47495 -.9224906
31 | -.2888544 .1530994 -1.89 0.059 -.58925 .0115413
32 | 1.156535 .1158735 9.98 0.000 .9291797 1.38389
33 | -1.056983 .1873764 -5.64 0.000 -1.424634 -.6893328
34 | 1.014261 .1694344 5.99 0.000 .6818145 1.346708
35 | .2376604 .1028197 2.31 0.021 .0359183 .4394024
36 | 1.326163 .1954298 6.79 0.000 .9427105 1.709615
37 | -.163333 .07354 -2.22 0.027 -.3076256 -.0190404
38 | -2.21564 .1491853 -14.85 0.000 -2.508356 -1.922924
39 | .5056484 .1683125 3.00 0.003 .1754032 .8358935
40 | .0443993 .0916846 0.48 0.628 -.1354947 .2242933
41 | .5380183 .154429 3.48 0.001 .2350138 .8410229
42 | .4905667 .1834165 2.67 0.008 .130686 .8504475
44 | .3712608 .2111512 1.76 0.079 -.0430381 .7855597
45 | -.1018475 .0772322 -1.32 0.188 -.2533845 .0496896
46 | -1.616425 .1324097 -12.21 0.000 -1.876225 -1.356624
47 | .512852 .0963999 5.32 0.000 .3237061 .7019979
48 | .4202159 .1942884 2.16 0.031 .0390035 .8014283
49 | -.2693639 .1521718 -1.77 0.077 -.5679395 .0292117
50 | -1.559857 .1811122 -8.61 0.000 -1.915216 -1.204497
51 | -.1249104 .0823236 -1.52 0.129 -.2864373 .0366164
53 | .2616721 .1387758 1.89 0.060 -.0106193 .5339635
54 | -.7122682 .1637362 -4.35 0.000 -1.033534 -.3910021
55 | -.0994233 .157224 -0.63 0.527 -.4079118 .2090653
56 | -1.283712 .1632931 -7.86 0.000 -1.604108 -.9633148
|
_cons | 2.373892 .5212183 4.55 0.000 1.351212 3.396572

```

```

-----*/
/* the estimate on shall law hasnt changed. let's go with time-fixed effect */
xtreg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, 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 = 0.2359                      min =      23
    between = 0.1358                     avg =     23.0
    overall = 0.1362                     max =      23

```

$F(30,50) = 40.77$   
 $\text{corr}(u_i, X_b) = 0.1441$        $\text{Prob} > F = 0.0000$

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

	Robust						
Inrob	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]		
incarc_rate	.0000314	.0003477	0.09	0.928	-.000667	.0007297	
pb1064	.0141078	.0840609	0.17	0.867	-.1547335	.1829491	
pw1064	-.0128322	.0327626	-0.39	0.697	-.0786379	.0529734	
pm1029	.1046049	.072997	1.43	0.158	-.0420138	.2512236	
avginc	.0143569	.0247676	0.58	0.565	-.0353903	.064104	
pop	.0000164	.0259374	0.00	0.999	-.0520805	.0521133	
density	-.0447449	.1982135	-0.23	0.822	-.4428684	.3533786	
shall	.0268298	.0521753	0.51	0.609	-.0779673	.1316269	
year							
78	.0328497	.0216897	1.51	0.136	-.0107154	.0764148	
79	.1375917	.032117	4.28	0.000	.0730828	.2021006	
80	.243408	.045464	5.35	0.000	.1520908	.3347251	
81	.2737088	.0508793	5.38	0.000	.1715147	.375903	
82	.21599	.0644109	3.35	0.002	.0866168	.3453632	
83	.1208158	.0867066	1.39	0.170	-.0533395	.2949711	
84	.078831	.1064308	0.74	0.462	-.1349416	.2926036	
85	.1131495	.1272629	0.89	0.378	-.1424655	.3687645	
86	.1895678	.1521449	1.25	0.219	-.1160242	.4951598	
87	.1572151	.1688872	0.93	0.356	-.1820049	.496435	
88	.1927596	.1878849	1.03	0.310	-.1846184	.5701376	
89	.2487313	.2140573	1.16	0.251	-.1812154	.6786781	
90	.3509806	.2668617	1.32	0.194	-.185027	.8869881	
91	.4668537	.2791767	1.67	0.101	-.0938891	1.027596	
92	.4633221	.2951262	1.57	0.123	-.1294562	1.0561	
93	.4796983	.3082342	1.56	0.126	-.1394084	1.098805	
94	.4943754	.3234124	1.53	0.133	-.1552175	1.143968	
95	.4940171	.3338462	1.48	0.145	-.1765328	1.164567	
96	.4341625	.3504351	1.24	0.221	-.2697072	1.138032	
97	.3652393	.3581743	1.02	0.313	-.354175	1.084654	
98	.2677144	.3690383	0.73	0.472	-.4735208	1.00895	
99	.1894683	.3845414	0.49	0.624	-.5829059	.9618425	
_cons	3.27912	1.676644	1.96	0.056	-.088518	6.646759	
sigma_u	.88484023						
sigma_e	.19352746						
rho	.95434775	(fraction of variance due to u_i)					

we can see that effect of shall law has decreased more. this model can be better because it explained for a lot of unobserved characteristics \*/

/\* we can check if the years are jointly significant or not

H0: effects of all time effects = 0

H1: effect not equal to 0 atleast for 1 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) = 25.86
Prob > F = 0.0000 */
```

```
/* Yes, the time effects are jointly statistically significant */
```

```
/* Also, the effect on shall law drops even more. so this model can be utilized to explain about the data. hence we prefer a model with both entity & time effect*/
```

```
/* random effects model */
```

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

```
/* Random-effects GLS regression Number of obs = 1,173
```

```
Group variable: stateid Number of groups = 51
```

```
R-sq: Obs per group:
```

```
within = 0.0269 min = 23
between = 0.5183 avg = 23.0
overall = 0.4910 max = 23
```

```
Wald chi2(8) = 83.85
```

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

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

```
-----+-----
| Robust
| lnrob | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
incarc_rate | .0001735 .0002507 0.69 0.489 -.0003179 .0006649
pb1064 | .1074485 .0337729 3.18 0.001 .0412548 .1736422
pw1064 | .0282639 .0162546 1.74 0.082 -.0035945 .0601223
pm1029 | .0252997 .0259436 0.98 0.329 -.0255489 .0761483
avginc | -.0152975 .0199351 -0.77 0.443 -.0543697 .0237747
pop | .0405861 .0244303 1.66 0.097 -.0072964 .0884686
density | .0997518 .0479974 2.08 0.038 .0056786 .1938251
shall | -.0411192 .0529293 -0.78 0.437 -.1448586 .0626203
_cons | 1.8759 1.025224 1.83 0.067 -.1335014 3.885301
-----+-----
```

```
sigma_u | .48469008
```

```
sigma_e | .21514885
```

```
rho | .83539542 (fraction of variance due to u_i)
```

```
*/
```

```
/* test for endogeneity - Hausman test */
```

```
quietly xtreg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, fe
estimates store fe
```

```
quietly xtreg lnrob incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, re
estimates store re
```

```
hausman fe re
```

```
/* ---- Coefficients ----
```

```
-----+-----
| (b) (B) (b-B) sqrt(diag(V_b-V_B))
| fe re Difference S.E.
-----+-----
incarc_rate | -.0000763 .0001735 -.0002498 .0000838
pb1064 | .1115421 .1074485 .0040936 .0153173
pw1064 | .0271807 .0282639 -.0010832 .
pm1029 | .0111817 .0252997 -.014118 .002718
avginc | -.0175195 -.0152975 -.002222 .0005277
pop | .0163332 .0405861 -.0242529 .00772
density | -.1860917 .0997518 -.2858435 .1008633
shall | -.0078189 -.0411192 .0333002 .
-----+-----
```

```
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)
= 26.94
```

```
Prob>chi2 = 0.0007
```



```

(V_b-V_B is not positive definite) */
/* reject null and conclude at least 1 has endogeneity. from the differences we can suspect density is an endogenous
variable */
/* ----- END of rob variable ----- */
/* ----- BEGIN of mur variable ----- */
use guns.dta
describe
/* create log variable for mur */
gen lnmur = log(mur)
/* let us check how only the shall law has an impact on mur rate */
reg lnmur shall
/* Source | SS      df    MS    Number of obs = 1,173
-----+----- F(1, 1171) = 106.51
Model | 48.346582    1 48.346582 Prob > F   = 0.0000
Residual | 531.555332 1,171 .45393282 R-squared   = 0.0834
-----+----- Adj R-squared = 0.0826
Total | 579.901914 1,172 .494796855 Root MSE   = .67375

-----+-----
lnmur |   Coef.   Std. Err.    t    P>|t|   [95% Conf. Interval]
-----+-----
shall | -.4733725   .0458686  -10.32  0.000   -.5633664   -.3833785
_cons | 1.897556   .0226094   83.93  0.000    1.853196    1.941915
-----+-----

```

We can see that, when shall law is implemented in a state, the violence rate drops by 47.3% \*/

/\* since we are employing regression on panel data, it is advised to use robust standard errors \*/

```

reg lnmur shall, vce(robust)
/* Linear regression
Number of obs = 1,173
F(1, 1171) = 95.12
Prob > F = 0.0000
R-squared = 0.0834
Root MSE = .67375

```

```

-----+-----
|           Robust
lnmur |   Coef.   Std. Err.    t    P>|t|   [95% Conf. Interval]
-----+-----
shall | -.4733725   .048536   -9.75  0.000   -.5685997   -.3781452
_cons | 1.897556   .0219606   86.41  0.000    1.854469    1.940642
-----+-----

```

We can observe changes in the t-values & standard errors but coefficients remain same. \*/

/\* let us go ahead and regress a pooled OLS model with robust standard errors

From the above model, we have to remove mur rob variables since they are highly correlated to vio, remodelling - \*/

```

reg lnmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, vce(robust)
/* Linear regression
Number of obs = 1,173
F(8, 1164) = 176.49
Prob > F = 0.0000
R-squared = 0.6059
Root MSE = .44312

```

```

-----+-----
|           Robust
lnmur |   Coef.   Std. Err.    t    P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | .002097   .0001544   13.58  0.000    .0017941    .0023999
pb1064 | .1307641   .018782    6.96  0.000    .0939137    .1676145
pw1064 | .0470796   .0090873    5.18  0.000    .0292502    .0649089
pm1029 | .0655308   .0136782    4.79  0.000    .0386941    .0923674
avginc | -.0772578   .0087513   -8.83  0.000   -.0944278   -.0600878
pop | .0416175   .0035077   11.86  0.000    .0347355    .0484995
density | .0396669   .0117541    3.37  0.001    .0166054    .0627284
shall | -.3131735   .0357019   -8.77  0.000   -.3832208   -.2431262
_cons | -2.485593   .6149912   -4.04  0.000   -3.692209   -1.278978
-----+-----

```

we can see that contribution of shall law towards mur rate has decreased. Now mur rate is reduced by 31% when a shall law was introduced. \*/

/\* Since it is panel data the least square estimators are not efficient. This is due to the fact that there can be unobserved heterogeneity.

We'll go ahead and create a fixed effect model & interpret the fixed effect estimators. We can do this in two ways - dummy variable creation or

fixed effect estimator. since N is large it isn't feasible to do so. Let's go ahead with fixed effect estimator.

```

We have to let stata know that we are dealing with panel data -*/
xtset stateid year
/* panel variable: stateid (strongly balanced)
time variable: year, 77 to 99
delta: 1 unit */
/* since it is a balanced panel data, it makes sense to use fixed effect over random effects */
xtreg lnmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, fe
/* Fixed-effects (within) regression      Number of obs   =   1,173
Group variable: stateid                  Number of groups  =    51
R-sq:                                Obs per group:
    within = 0.1528                      min =      23
    between = 0.2221                     avg =     23.0
    overall = 0.1846                     max =      23

                                F(8,1114)    =    25.12
corr(u_i, Xb) = -0.8961          Prob > F      =   0.0000

```

```

-----+-----
lnmur |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.00036   .0001278   -2.82   0.005   -.0006107   -.0001093
pb1064 | .0307009   .0242419    1.27   0.206   -.0168641   .0782658
pw1064 | .0103313   .006928    1.49   0.136   -.003262    .0239246
pm1029 | .0392384   .0087427    4.49   0.000   .0220844   .0563923
avginc | .0243114   .0080663    3.01   0.003   .0084846   .0401382
pop | -.0257054   .0119103   -2.16   0.031   -.0490745   -.0023363
density | -.6707132   .1160957   -5.78   0.000   -.898504   -.4429224
shall | -.06081   .0257579   -2.36   0.018   -.1113495   -.0102704
_cons | .4600088   .5253095    0.88   0.381   -.5706989   1.490716
-----+-----
sigma_u | 1.36035
sigma_e | .21942693
rho | .97464151 (fraction of variance due to u_i)

```

```

F test that all u_i=0: F(50, 1114) = 72.66          Prob > F = 0.0000
We can see that the coefficient of shall rate has reduced considerably. If there is unobserved heterogeneity, we can make
our model robust to these effects as well - */
xtreg lnmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall, 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 = 0.1528                      min =      23
    between = 0.2221                     avg =     23.0
    overall = 0.1846                     max =      23

                                F(8,50)      =   156.39
corr(u_i, Xb) = -0.8961          Prob > F      =   0.0000
                                (Std. Err. adjusted for 51 clusters in stateid)

```

```

-----+-----
|               Robust
lnmur |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.00036   .0004231   -0.85   0.399   -.0012099   .0004899
pb1064 | .0307009   .0781245    0.39   0.696   -.1262169   .1876186
pw1064 | .0103313   .0128776    0.80   0.426   -.0155341   .0361967
pm1029 | .0392384   .0215964    1.82   0.075   -.0041394   .0826161
avginc | .0243114   .0156779    1.55   0.127   -.0071786   .0558013
pop | -.0257054   .0203457   -1.26   0.212   -.0665709   .0151602
density | -.6707132   .3957745   -1.69   0.096   -1.46565   .1242232
shall | -.06081   .0369632   -1.65   0.106   -.1350527   .0134327
_cons | .4600088   .8425884    0.55   0.588   -1.23238   2.152397
-----+-----
sigma_u | 1.36035
sigma_e | .21942693
rho | .97464151 (fraction of variance due to u_i)

```

```

-----+----- */
/* we can have 2 more variations for fixed effects. entity fixed & time fixed effects. We'll good ahead with both */
/* fixed entity fixed effect. create dummy variable for state */
reg lnmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.stateid
/* Source |   SS      df   MS      Number of obs   =   1,173
-----+----- F(58, 1114)    =   188.45

```

```

Model | 526.264844    58 9.07353179 Prob > F    = 0.0000
Residual | 53.6370704    1,114 .048148178 R-squared    = 0.9075
-----+----- Adj R-squared = 0.9027
Total | 579.901914    1,172 .494796855 Root MSE    = .21943
-----+-----

Inmur |   Coef. Std. Err.   t  P>|t|   [95% Conf. Interval]
-----+-----
incarc_rate | -.00036 .0001278  -2.82 0.005  -.0006107 -.0001093
pb1064 | .0307009 .0242419   1.27 0.206  -.0168641 .0782658
pw1064 | .0103313 .006928   1.49 0.136  -.003262 .0239246
pm1029 | .0392384 .0087427   4.49 0.000   .0220844 .0563923
avginc | .0243114 .0080663   3.01 0.003   .0084846 .0401382
pop | -.0257054 .0119103  -2.16 0.031  -.0490745 -.0023363
density | -.6707132 .1160957  -5.78 0.000  -.898504 -.4429224
shall | -.06081 .0257579  -2.36 0.018  -.1113495 -.0102704
|
stateid |
2 | -.5647602 .0992828  -5.69 0.000  -.7595625 -.3699578
4 | -.2651784 .1211918  -2.19 0.029  -.5029684 -.0273885
5 | -.187964 .0907612  -2.07 0.039  -.3660462 -.0098819
6 | .5355069 .3145871   1.70 0.089  -.0817431 1.152757
8 | -.8074469 .1531466  -5.27 0.000  -1.107935 -.5069587
9 | -.6007435 .1840818  -3.26 0.001  -.9619296 -.2395574
10 | -.829185 .1047633  -7.91 0.000  -1.034741 -.6236295
11 | 7.77904 1.064525   7.31 0.000   5.69034 9.86774
12 | .3369919 .1549863   2.17 0.030   .032894 .6410899
13 | .0527886 .0735155   0.72 0.473  -.0914558 .1970331
15 | -1.294748 .3536591  -3.66 0.000  -1.988661 -.6008354
16 | -1.280885 .1666717  -7.69 0.000  -1.607911 -.9538593
17 | .0662671 .1463662   0.45 0.651  -.2209174 .3534515
18 | -.3334492 .1516256  -2.20 0.028  -.6309531 -.0359453
19 | -1.739756 .1744191  -9.97 0.000  -2.081983 -1.397529
20 | -.7768745 .1386567  -5.60 0.000  -1.048932 -.5048169
21 | -.3966237 .1432174  -2.77 0.006  -.6776299 -.1156175
22 | .3453888 .0781619   4.42 0.000   .1920277 .4987499
23 | -1.633723 .1816275  -8.99 0.000  -1.990094 -1.277353
24 | .0639087 .0808585   0.79 0.429  -.0947435 .2225608
25 | -.8014337 .2034003  -3.94 0.000  -1.200525 -.4023427
26 | .0231729 .1353962   0.17 0.864  -.2424873 .2888331
27 | -1.525127 .1709097  -8.92 0.000  -1.860468 -1.189786
28 | .047795 .1052837   0.45 0.650  -.1587817 .2543717
29 | -.1471592 .1258841  -1.17 0.243  -.3941559 .0998375
30 | -1.159839 .1435823  -8.08 0.000  -1.441561 -.8781166
31 | -1.337181 .1561436  -8.56 0.000  -1.64355 -1.030812
32 | -.0583977 .1181776  -0.49 0.621  -.2902734 .173478
33 | -1.747664 .1911023  -9.15 0.000  -2.122625 -1.372703
34 | -.112379 .1728035  -0.65 0.516  -.451436 .226678
35 | -.2073594 .1048642  -1.98 0.048  -.4131129 -.0016058
36 | .4095608 .1993158   2.05 0.040   .0184842 .8006375
37 | -.1033656 .0750023  -1.38 0.168  -.2505274 .0437961
38 | -2.39921 .1521517  -15.77 0.000  -2.697746 -2.100673
39 | -.3293598 .1716592  -1.92 0.055  -.6661717 .007452
40 | -.3157795 .0935077  -3.38 0.001  -.4992506 -.1323084
41 | -.9237303 .1574997  -5.86 0.000  -1.23276 -.6147007
42 | -.299992 .1870636  -1.60 0.109  -.6670287 .0670447
44 | -.6714586 .2153498  -3.12 0.002  -1.093996 -.2489217
45 | -.1236207 .0787679  -1.57 0.117  -.2781709 .0309296
46 | -1.889717 .1350426  -13.99 0.000  -2.154683 -1.62475
47 | -.0904587 .0983168  -0.92 0.358  -.2833656 .1024483
48 | .380945 .1981517   1.92 0.055  -.0078475 .7697376
49 | -1.363478 .1551976  -8.79 0.000  -1.667991 -1.058966
50 | -1.650036 .1847135  -8.93 0.000  -2.012462 -1.287611
51 | -.3505359 .0839606  -4.18 0.000  -.5152746 -.1857972
53 | -.8461956 .1415353  -5.98 0.000  -1.123901 -.5684898
54 | -.6978991 .166992  -4.18 0.000  -1.025553 -.3702449
55 | -1.154587 .1603503  -7.20 0.000  -1.46921 -.8399648
56 | -1.145291 .1665401  -6.88 0.000  -1.472059 -.8185238
|
_cons | .8937583 .5315823   1.68 0.093  -.1492571 1.936774
-----+----- */

```

```

/* the estimate on shall law hasnt changed. let's go with time-fixed effect */
xtreg Inmur incarc_rate pb1064 pw1064 pm1029 avginc pop density shall i.year, 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 = 0.2905                      min =      23
    between = 0.1945                     avg =     23.0
    overall = 0.1413                     max =      23

```

```

                                F(30,50)    =   81.49
corr(u_i, Xb) = -0.8336          Prob > F    =   0.0000

```

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

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
incarc_rate	-.0001164	.0003631	-0.32	0.750	-.0008457 .0006129
pb1064	.0219833	.0758151	0.29	0.773	-.1302958 .1742624
pw1064	-.0004893	.0201044	-0.02	0.981	-.0408701 .0398915
pm1029	.0691941	.0417945	1.66	0.104	-.0147526 .1531408
avginc	.0566492	.0165554	3.42	0.001	.0233967 .0899017
pop	-.0320769	.0209819	-1.53	0.133	-.0742202 .0100664
density	-.5442635	.3192203	-1.70	0.094	-1.185436 .0969093
shall	-.0149524	.0382403	-0.39	0.697	-.0917603 .0618556
year					
78	-.0007195	.0322722	-0.02	0.982	-.0655401 .0641011
79	.0592481	.0311141	1.90	0.063	-.0032465 .1217427
80	.0901814	.041058	2.20	0.033	.0077139 .1726489
81	.1021543	.0510636	2.00	0.051	-.00041 .2047186
82	.0224098	.0581861	0.39	0.702	-.0944604 .1392799
83	-.0314385	.0640621	-0.49	0.626	-.1601111 .0972341
84	-.1359192	.071662	-1.90	0.064	-.2798565 .0080181
85	-.0866144	.0856965	-1.01	0.317	-.2587409 .0855122
86	-.0122752	.0927286	-0.13	0.895	-.1985262 .1739758
87	-.0290338	.0999408	-0.29	0.773	-.2297707 .1717032
88	-.0174594	.1196893	-0.15	0.885	-.2578626 .2229437
89	-.0145617	.1321034	-0.11	0.913	-.2798993 .2507759
90	.059998	.1649718	0.36	0.718	-.2713577 .3913537
91	.1053071	.1754909	0.60	0.551	-.2471767 .4577909
92	.0681002	.1828352	0.37	0.711	-.2991352 .4353355
93	.1544297	.1898113	0.81	0.420	-.2268176 .535677
94	.0442648	.1971908	0.22	0.823	-.3518047 .4403342
95	.0556601	.1989082	0.28	0.781	-.3438588 .455179
96	-.015709	.2125365	-0.07	0.941	-.4426011 .4111831
97	-.1221824	.2186706	-0.56	0.579	-.5613952 .3170304
98	-.1863381	.2332966	-0.80	0.428	-.6549281 .2822519
99	-.2554286	.2420434	-1.06	0.296	-.741587 .2307298
_cons	.1882653	1.056771	0.18	0.859	-1.934322 2.310853
sigma_u	1.1362086				
sigma_e	.20281999				
rho	.96911961				(fraction of variance due to u_i)

we can see that effect of shall law has decreased more. this model can be better because it explained for a lot of unobserved characteristics \*/

/\* we can check if the years are jointly significant or not

H0: effects of all time effects = 0

H1: effect not equal to 0 at least for 1 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) = 19.61

Prob > F = 0.0000 \*/

/\* Yes, the time effects are jointly statistically significant \*/

/\* Also, the effect on shall law drops even more. so this model can be utilized to explain about the data. hence we prefer a model with both entity & time effect\*/

/\* random effects model \*/

xtreg lnmur incarc\_rate pb1064 pw1064 pm1029 avginc pop density shall, re cluster(stateid)

/\* Random-effects GLS regression Number of obs = 1,173

Group variable: stateid Number of groups = 51

R-sq:

Obs per group:

```
within = 0.0813      min = 23
between = 0.4921     avg = 23.0
overall = 0.4381     max = 23
```

Wald chi2(8) = 277.18

corr(u\_i, X) = 0 (assumed) Prob > chi2 = 0.0000

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

```
-----+-----
      |      Robust
Inmur |      Coef. Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
incarc_rate | .0004438 .0004395   1.01  0.313   -.0004176   .0013051
pb1064 | .0512656 .0376346   1.36  0.173   -.0224967   .125028
pw1064 | .0069318 .0123563   0.56  0.575   -.0172861   .0311497
pm1029 | .0734716 .0229191   3.21  0.001   .0285511   .1183922
avginc | .0093982 .0149265   0.63  0.529   -.0198572   .0386535
pop | .0029126 .0114322   0.25  0.799   -.0194941   .0253193
density | .0163429 .067886   0.24  0.810   -.1167113   .1493971
shall | -.1153705 .039896  -2.89  0.004   -.1935652   -.0371757
_cons | -.3301384 .7279221  -0.45  0.650   -1.75684   1.096563
-----+-----
```

sigma\_u | .30755149

sigma\_e | .21942693

rho | .66267693 (fraction of variance due to u\_i)

\*/

/\* test for endogeneity - Hausman test \*/

quietly xtreg lnmur incarc\_rate pb1064 pw1064 pm1029 avginc pop density shall, fe estimates store fe

quietly xtreg lnmur incarc\_rate pb1064 pw1064 pm1029 avginc pop density shall, re estimates store re

hausman fe re

/\* ---- Coefficients ----

```
-----+-----
      | (b)      (B)      (b-B)      sqrt(diag(V_b-V_B))
      | fe      re      Difference      S.E.
-----+-----
incarc_rate | -.00036 .0004438  -.0008037   .0000882
pb1064 | .0307009 .0512656  -.0205648   .017453
pw1064 | .0103313 .0069318   .0033995    .
pm1029 | .0392384 .0734716  -.0342333   .0024109
avginc | .0243114 .0093982   .0149132    .
pop | -.0257054 .0029126  -.0286179   .0094248
density | -.6707132 .0163429  -.6870561   .1096429
shall | -.06081 -.1153705   .0545605    .
-----+-----
```

-----  
*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)*  
*= 91.44*  
*Prob>chi2 = 0.0000*  
*(V\_b-V\_B is not positive definite) \*/*

*/\* reject null and conclude at least 1 has endogeneity. from the differences we can suspect density is an endogenous variable \*/*

\*\*\*\*\* END OF STATA CODE \*\*\*\*\*  
\*\*\*\*\* BEGIN OF SAS CODE \*\*\*\*\*

```
data guns;
infile "H:\econ\project\guns.dta" firstobs=2;
input year vio mur rob incarc_rate pbl064 pwl064 pml029 pop avginc density stateid shall;
run;
```

```
data guns;
set guns;
lnvio = log(vio);
run;
```

```
proc reg data=guns;
model lnvio = incarc_rate pb1064 pw1064 pm1029 pop avginc density shall;
plot residual.*incarc_rate;
plot residual.*pb1064;
plot residual.*pw1064;
plot residual.*pm1029;
plot residual.*pop;
plot residual.*avginc;
plot residual.*density;
run;
```

\*\*\*\*\* END OF SAS CODE \*\*\*\*\*

\*\*\*\*\* BEGIN OF REPORT \*\*\*\*\*