2019

Impact of Shall law on crime Rate in the US

SUBMITTD BY:

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INTRODUCTION:

The report consists of how law and incarceration rate effects the crime rate in the US from the year 1977 to 1999. Crime in the US has been segregated into 3 categories namely **Violent** crime rate, **Robbery** rate, and **Murder** rate.

After looking at the analysis, these laws have different effects on the three variables. Apart from this, we have other independent variables such as incarc_rate, which tells me about the incarceration rate in the state in the previous year. The density is the population per square mile of land area. Pm1029 which is the percent of the state population, which is male, ages 10-29, pm1064 is the percentage of the state population that is black, age 10 to 64 and pw1064, percentage of the population that is white, age 10 to 64.

DATA:

For our research, we will be looking at historical data from 1977-1999. We will be judging the panel data for 51 states during this time to justify whether the shall-issue law positively affects violent crime. We will be using various visualizations to identify patterns, high crime rate areas and relationships across different factors that affect the crime rate. We will also conduct regression analysis using several models to identify the effect of shall-issue law on the crime rate.

POTENTIALLY SIGNIFICANT VARIABLES NOT GIVEN IN THE DATASET:

Not all the variables that affect the crime rate are included in the data. Variables like demographics, the cultural attitude of people are some of the entity fixed effects that influence the crime rate. This entity fixed effects will be taken care of if we use a Fixed Effect Model.

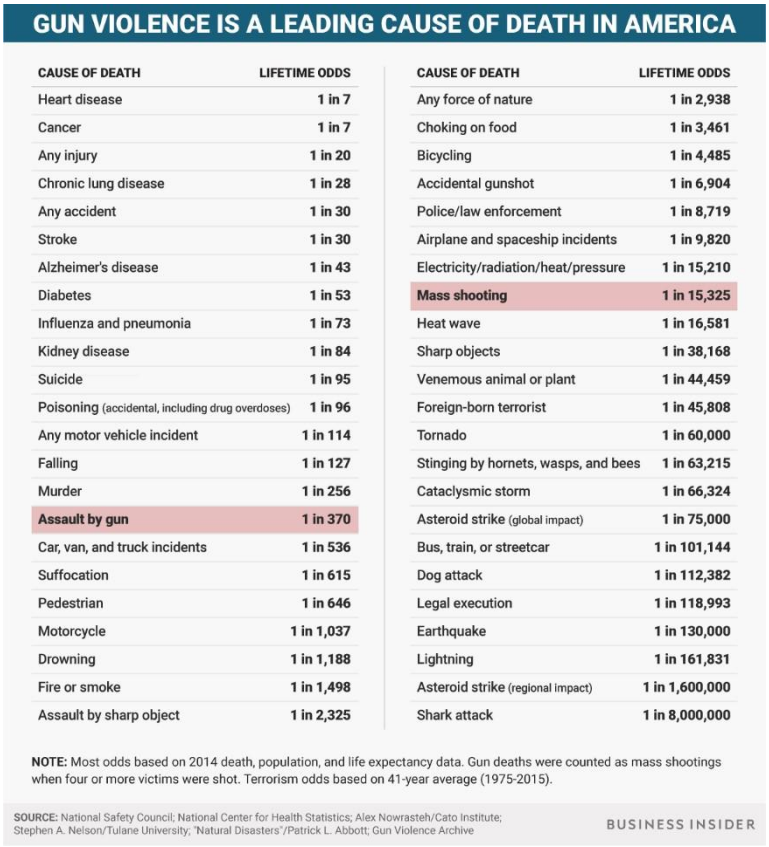
WHY ARE WE CONDUCTING THE ANALYSIS?

The impact of guns on crime in the US has triggered a lot of debate in America. As a result, 29 states in the US have passed the right-to-carry-law. We need to analyze the historical data on crime and the impact shall law has on it. This analysis will give a clear picture of whether the shall law has any impact on the crime rate or not.

WHAT IS SHALL LAW?

The shall issue law mandates that the government must issue a concealed carry handgun permits to those that meet the relevant criteria. This falls on the opposite end of the spectrum of gun control laws. The national rifle association is one of the key proponents of the shall-issue law.

As of November 14th, of this year, there have been a total of 366 mass shootings in the US in 2019 alone. Americans are more likely to die from gun violence than drowning, fire, stabbing, choking, airplanes, animal attacks, and forces of nature – combined.



GUN VIOLENCE IS A LEADING CAUSE OF DEATH IN AMERICA

CAUSE OF DEATH	LIFETIME ODDS
Heart disease	1 in 7
Cancer	1 in 7
Any injury	1 in 20
Chronic lung disease	1 in 28
Any accident	1 in 30
Stroke	1 in 30
Alzheimer's disease	1 in 43
Diabetes	1 in 53
Influenza and pneumonia	1 in 73
Kidney disease	1 in 84
Suicide	1 in 95
Poisoning (accidental, including drug overdoses)	1 in 96
Any motor vehicle incident	1 in 114
Falling	1 in 127
Murder	1 in 256
Assault by gun	**1 in 370**
Car, van, and truck incidents	1 in 536
Suffocation	1 in 615
Pedestrian	1 in 646
Motorcycle	1 in 1,037
Drowning	1 in 1,188
Fire or smoke	1 in 1,498
Assault by sharp object	1 in 2,325

CAUSE OF DEATH	LIFETIME ODDS
Any force of nature	1 in 2,938
Choking on food	1 in 3,461
Bicycling	1 in 4,485
Accidental gunshot	1 in 6,904
Police/law enforcement	1 in 8,719
Airplane and spaceship incidents	1 in 9,820
Electricity/radiation/heat/pressure	1 in 15,210
Mass shooting	**1 in 15,325**
Heat wave	1 in 16,581
Sharp objects	1 in 38,168
Venemous animal or plant	1 in 44,459
Foreign-born terrorist	1 in 45,808
Tornado	1 in 60,000
Stinging by hornets, wasps, and bees	1 in 63,215
Cataclysmic storm	1 in 66,324
Asteroid strike (global impact)	1 in 75,000
Bus, train, or streetcar	1 in 101,144
Dog attack	1 in 112,382
Legal execution	1 in 118,993
Earthquake	1 in 130,000
Lightning	1 in 161,831
Asteroid strike (regional impact)	1 in 1,600,000
Shark attack	1 in 8,000,000

NOTE: Most odds based on 2014 death, population, and life expectancy data. Gun deaths were counted as mass shootings when four or more victims were shot. Terrorism odds based on 41-year average (1975-2015).

SOURCE: National Safety Council; National Center for Health Statistics; Alex Nowrasteh/Cato Institute; Stephen A. Nelson/Tulane University; "Natural Disasters"/Patrick L. Abbott; Gun Violence Archive

BUSINESS INSIDER

I. VARIABLE DEFINITIONS

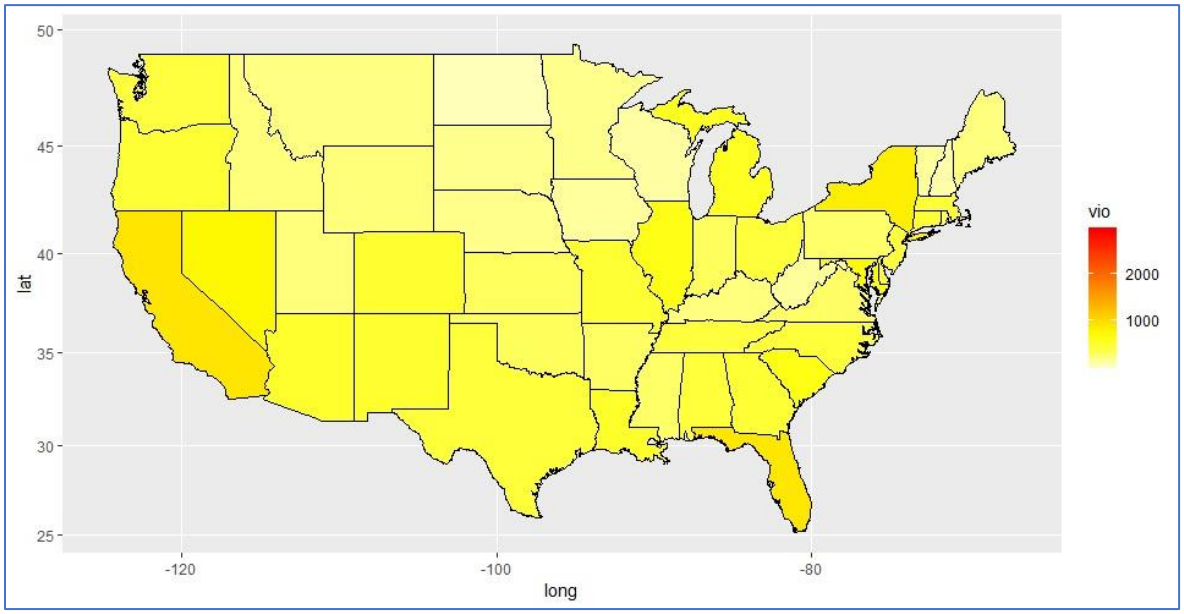
Variable	Definition
vio	violent crime rate (incidents per 100,000 members of the population)
rob	robbery rate (incidents per 100,000)
mur	murder rate (incidents per 100,000)
shall	= 1 if the state has a shall-carry law in effect in that year = 0 otherwise
incarc_rate	incarceration rate in the state in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

A **balanced panel** is a dataset in which each panel member or each entity is observed every year. Consequently, if a balanced panel contains N panel members and T periods, the number of observations (n) in the dataset is necessarily $n = N \times T$.

Total observations = 51 states × 23 years = 1173 observations.

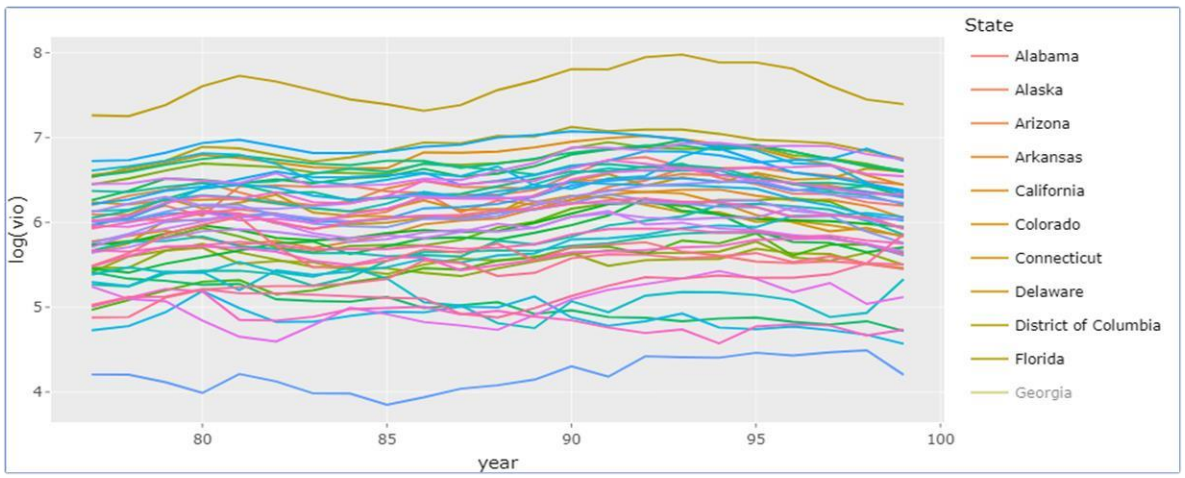
II. EXPLORATORY DATA ANALYSIS

A HEAT MAP FOR VIOLENCE RATE ACROSS 51 STATES IN US



Observation: The above heat map shows me the violence rate across different state in the US from the year 1977-1999. The violence rate is highest in the District of Columbia.

A line graph of Violent crime rate for 23 years across 51 States

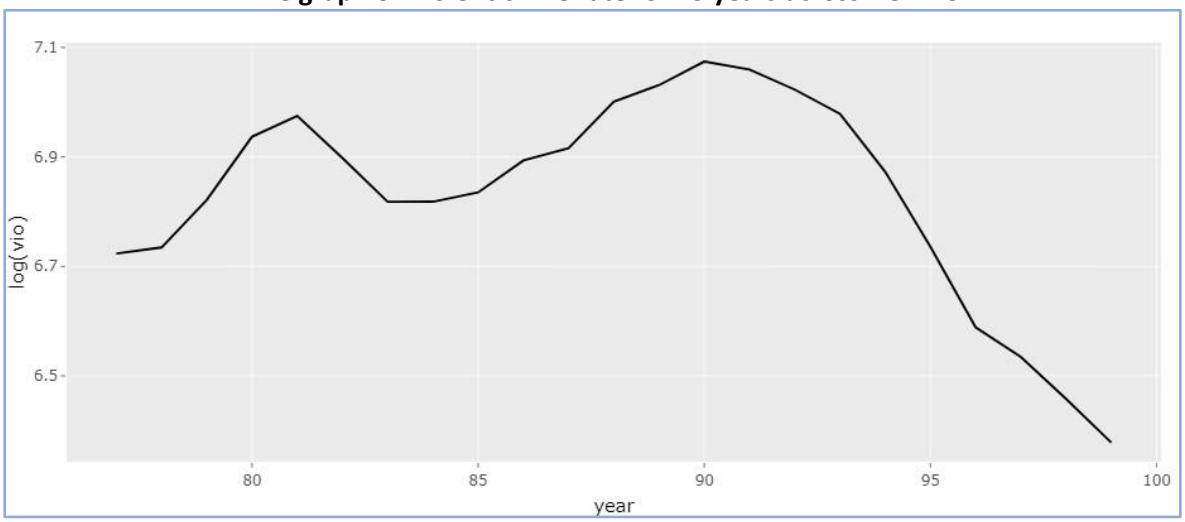


We have taken the log of violent crim rate so that the skewness of the data can be controlled as some of the values are very high that can bias the observations.

Observation: District of Columbia is the one with the highest crime rate. There is a dip in the Violence Crime rate in for almost all the states starting from 1990.

Example: We can see that New York had a dip in the crime rate from the year 1990. The violence rate in 1990 was 7.07 which then decreased to 6.4. We can see a similar trend in Rhode Island and almost all the states where the violence rate has been dipping starting from the 1990s.

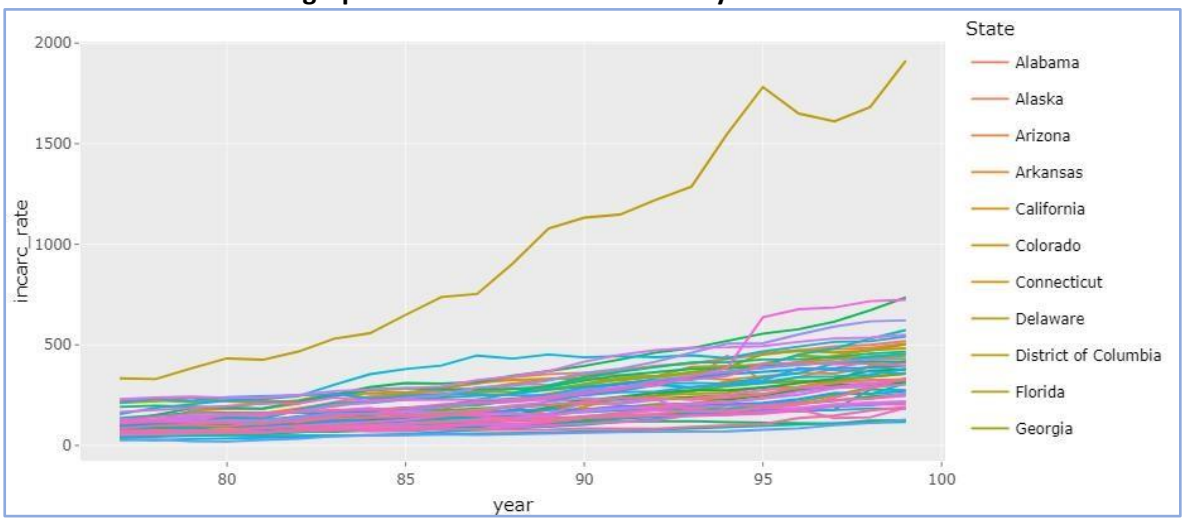
A line graph of Violent crime rate for 23 years across New York



Following are the possible reasons for the dip in Violence Crime rate:

1) INCARCERATION RATE(incarc_rate):

A line graph of Incarceration rate for 23 years across 51 States



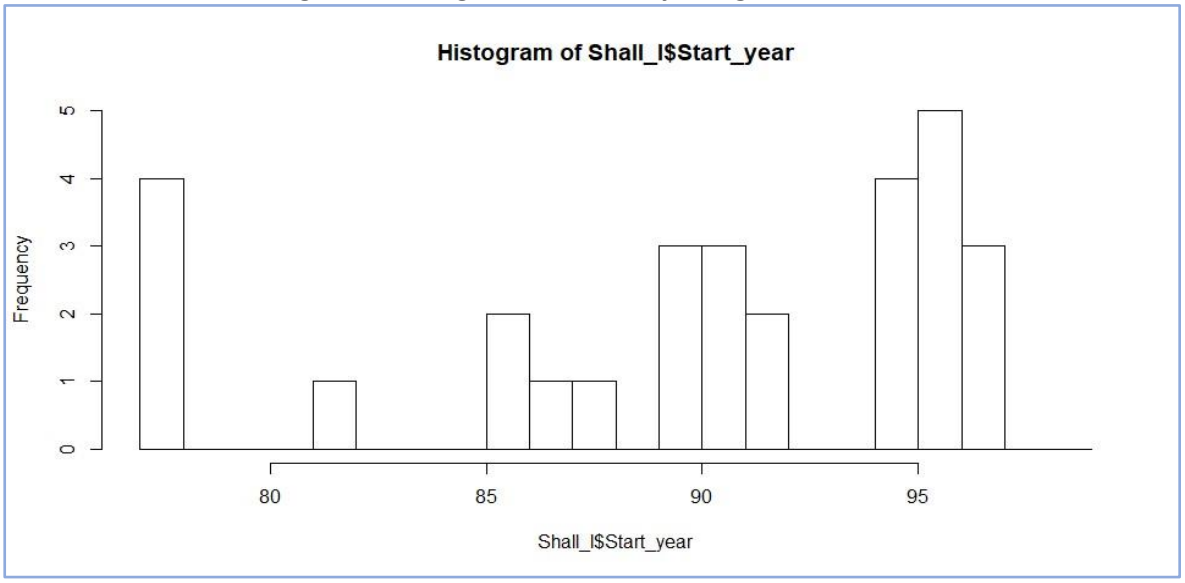
Observation: From the above plot, we can observe that the incarceration rate has increased from the 1990s. This is in line with the pattern observed for the Violent crime rate. If there are more criminals in jail, then there are fewer criminals on the streets which will eventually lead to a low crime rate.

Economic Theory: The United States imprisons more people than anywhere else in the world, both in relative and total numbers. [link..]

2)SHALL LAW(shall):

In the given data, shall is an indicator variable, i.e. shall=1, if the state has issued shall law and 0, if the state has not issued the shall law.

Histogram showing Shall law issue year against no. of states:

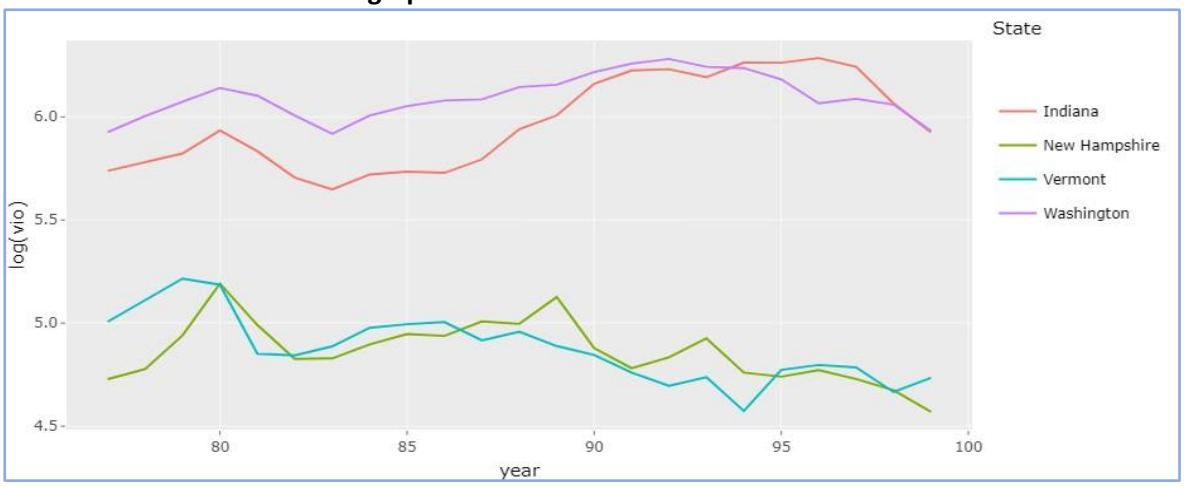


Observation: Most of the states have implemented the shall law after 1990. Shall law might be a possible reason why the crime rate decreased in the 1990s.

CASE 1: State having law effective from the beginning i.e. 1977

State ID	Year	State	Shall
18	77	Indiana	1
33	77	New Hampshire	1
50	77	Vermont	1
53	77	Washington	1

A line graph of Violence Rate for the above 4 states

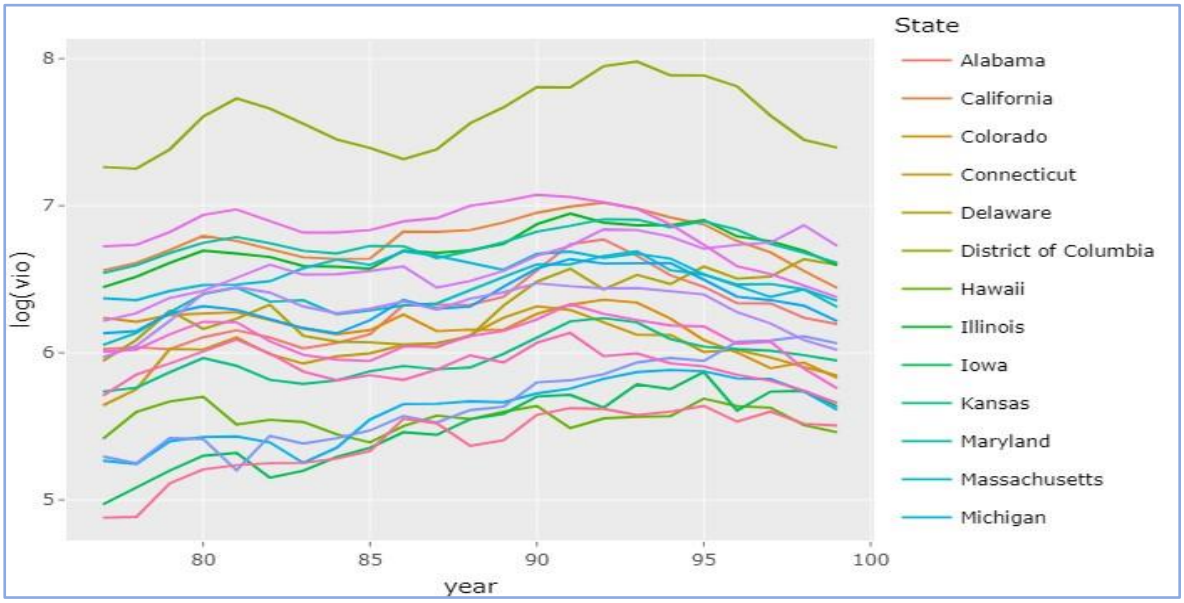


Observation: We can observe a similar pattern i.e. the crime rates are decreasing after the year 1990.

CASE 2: States that never had the shall law implemented

States					
Alabama	Delaware	Iowa	Michigan	New Jersey	Rhode Island
California	District of Columbia	Kansas	Minnesota	New Mexico	Wisconsin
Colorado	Hawaii	Maryland	Missouri	New York	
Connecticut	Illinois	Massachusetts	Nebraska	Ohio	

A line graph of Violence Rate for the above 22 states

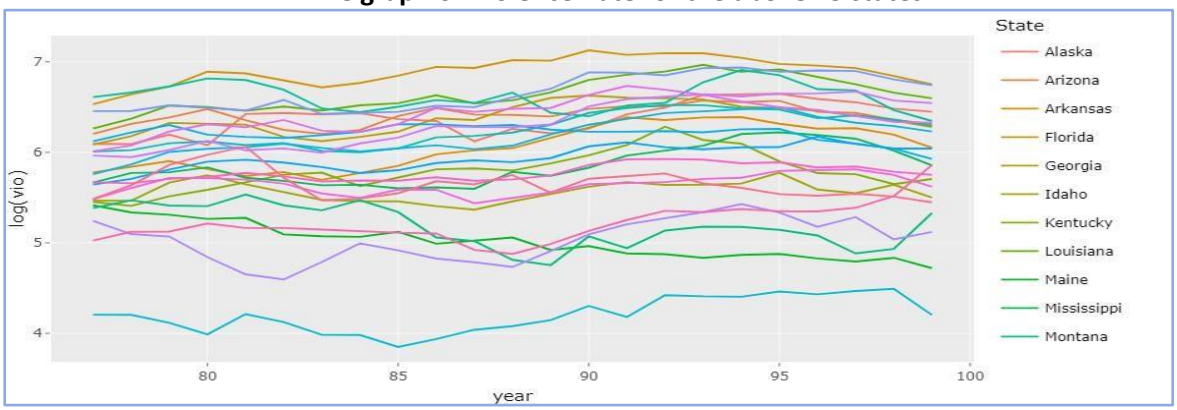


Observation: Even for states that never implemented the law, we see a similar pattern as we saw for the states where the law was effective since 1977.

CASE 3: States that implemented the law after a few years

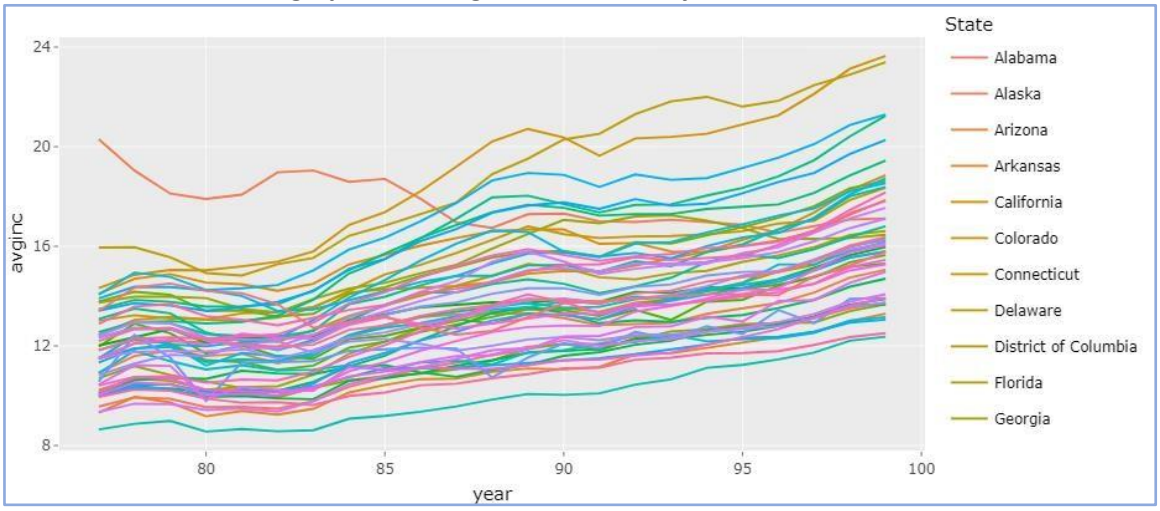
States						
Alaska	Georgia	Maine	North Carolina	Pennsylvania	Texas	Wyoming
Arizona	Idaho	Mississippi	North Dakota	South Carolina	Utah	
Arkansas	Kentucky	Montana	Oklahoma	South Dakota	Virginia	
Florida	Louisiana	Nevada	Oregon	Tennessee	West Virginia	

A line graph of Violence Rate for the above 25 states



3) Average Income (avginc):

A line graph of Average income for 23 years across 51 States

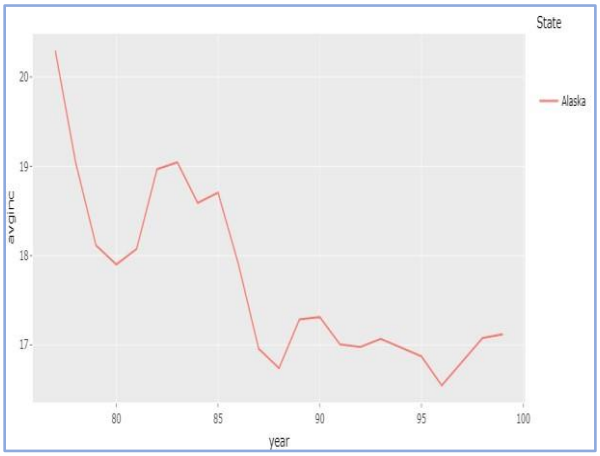


Observation: We can observe that the average income has a positive relationship with the year. This is due to the economic growth in the US in the 1990s

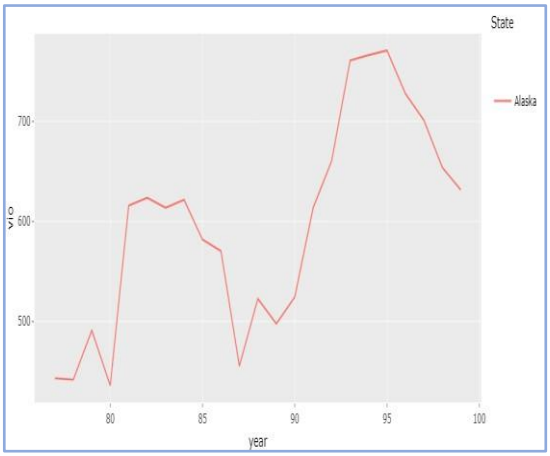
ECONOMIC THEORY: From 1990 to 1999, the median American household income grew by 10 percent. The United States economy grew by an average of 4 percent per year between 1992 and 1999. During the '90s, stocks quadrupled in value - the Dow Jones industrial average increased by 309 percent. [link..]

Outlier: **Alaska**

Average Income of Alaska



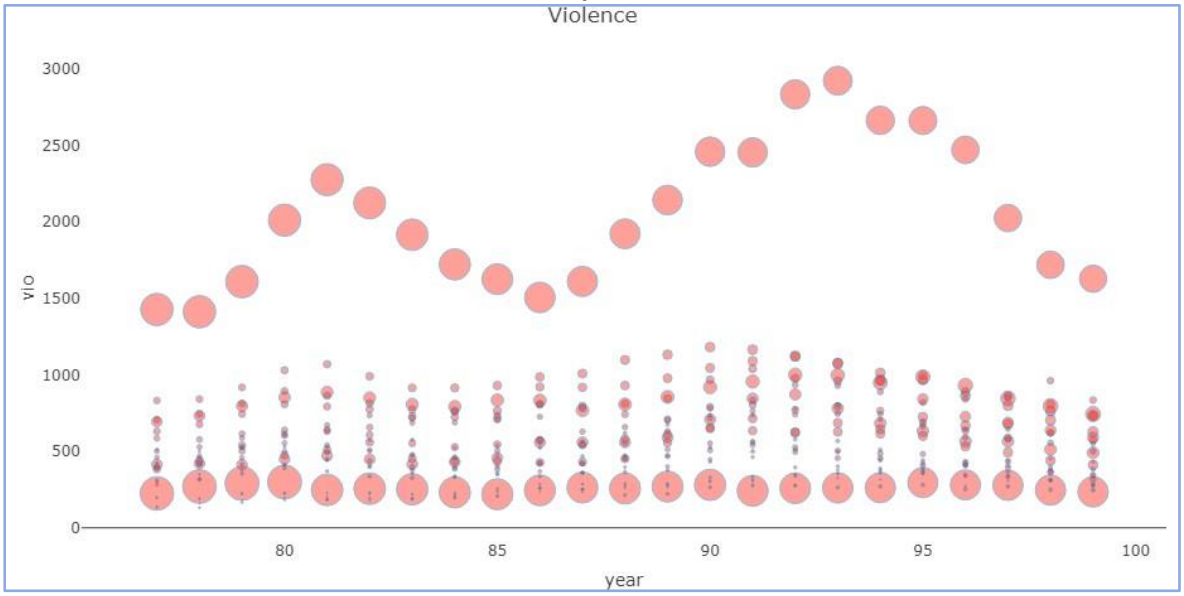
Violence rate in Alaska



Observation: The shall law was implemented in Alaska in the year 1995 which is why we can see a dip in crime rate. By looking at the above graph we can say that shall law might have played a very important role in controlling the crime rate.

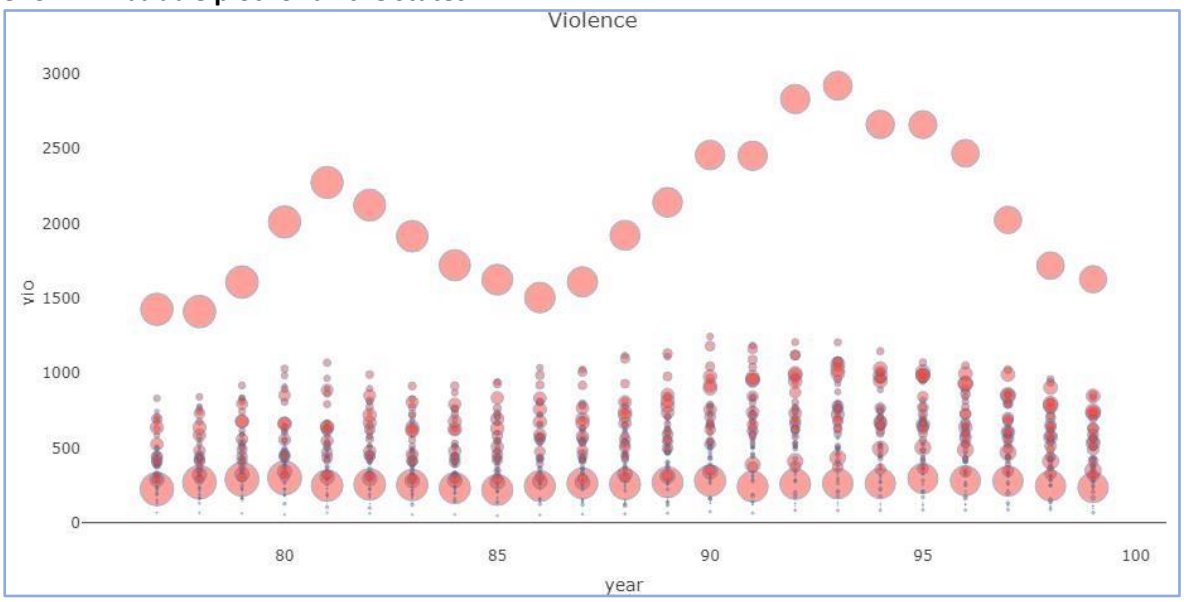
4) Black Race(pb1064):

Case 1: States where the shall law was never implemented



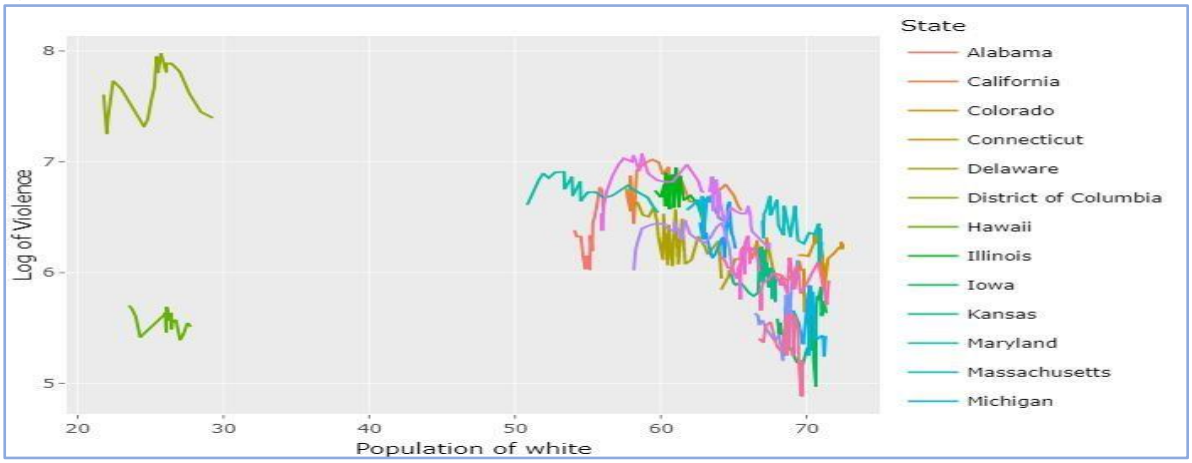
Observation: We can observe that the black population in the District of Columbia is the 2nd highest and even the crime rate is very high, but for Hawaii, even though the crime rate is low, it has the highest black population among the states that have not implemented the law ever.

CASE 2: A bubble plot for all the states

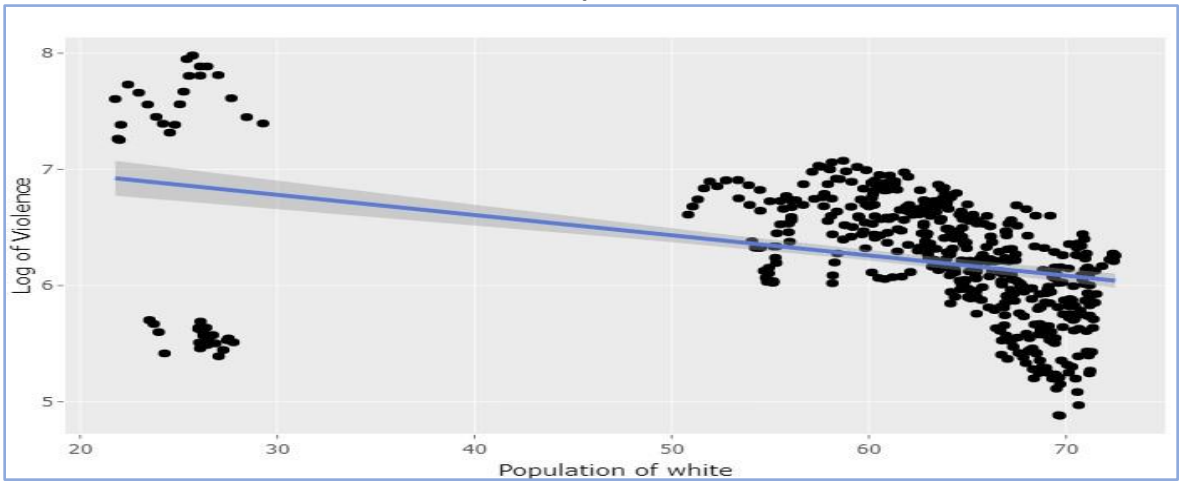


Observation: From the above graph, we can't say for sure if having higher black population plays an important role in the increase/decrease of the violence rate.

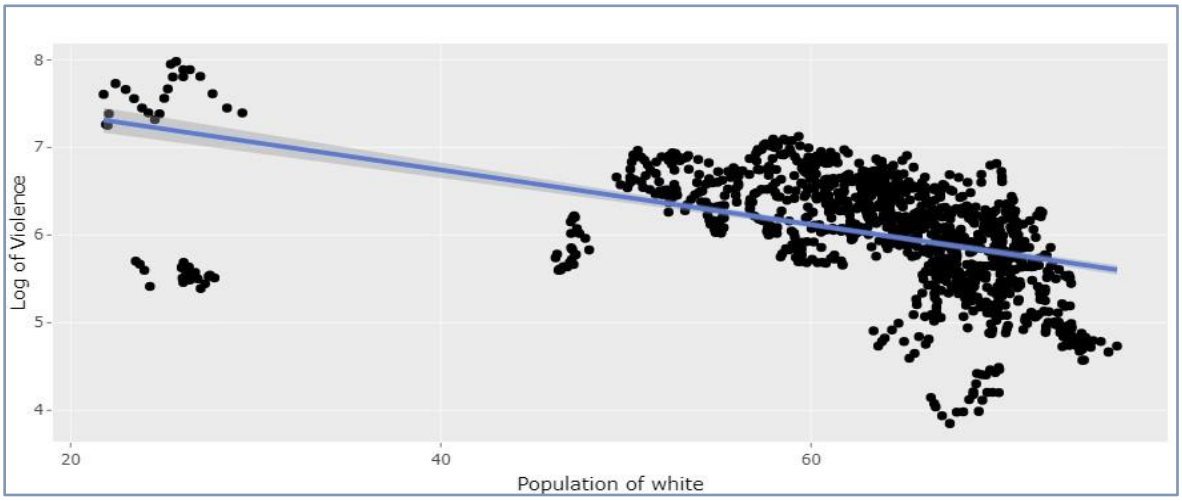
5) WHITE RACE:



Case 1: States where the shall law was never implemented

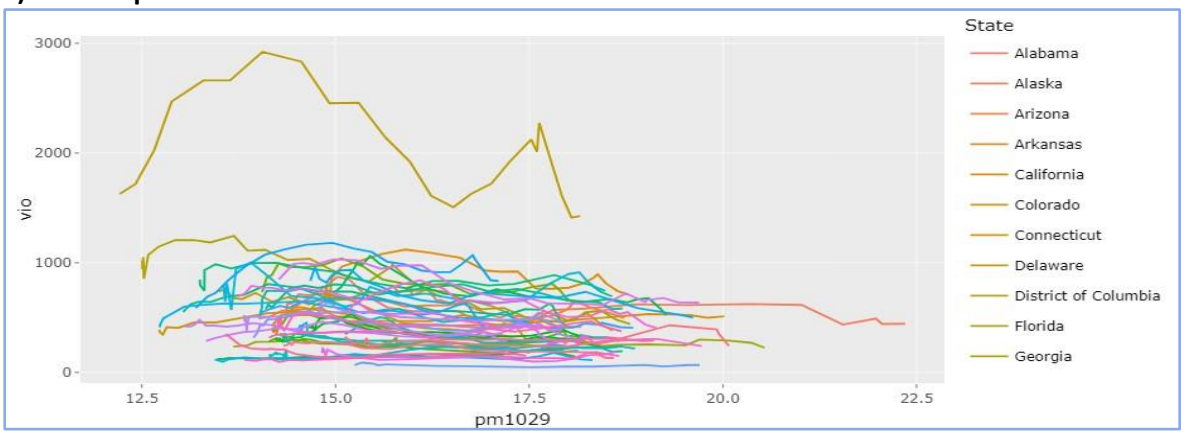


Case2: A scatter plot for all the states

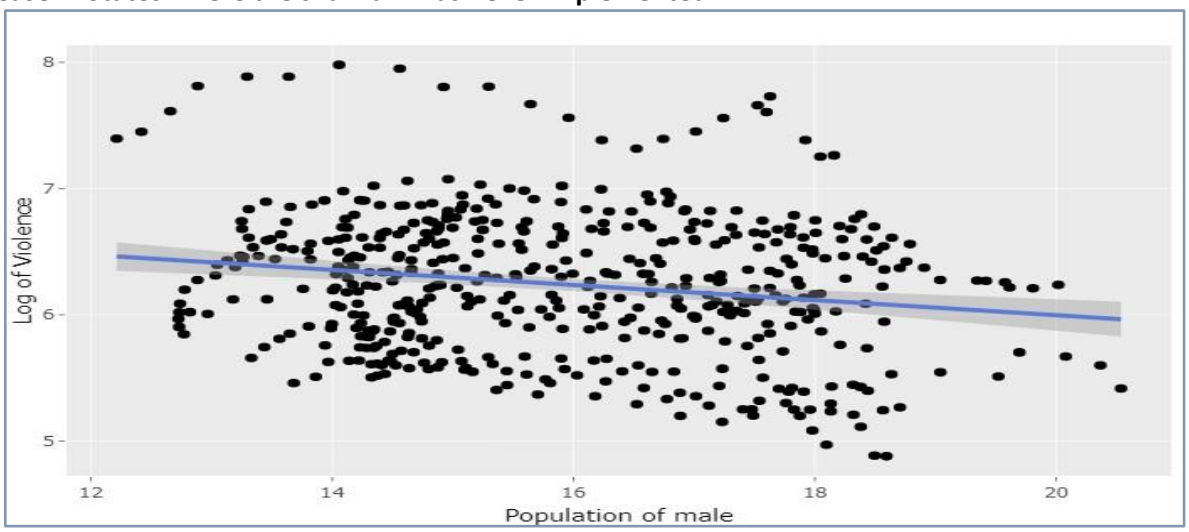


Observation: We can observe in both the graphs that most of the states have a higher white population except for Hawaii and District of Columbia. Also, we can see a negative relationship of white population with the violence crime rate.

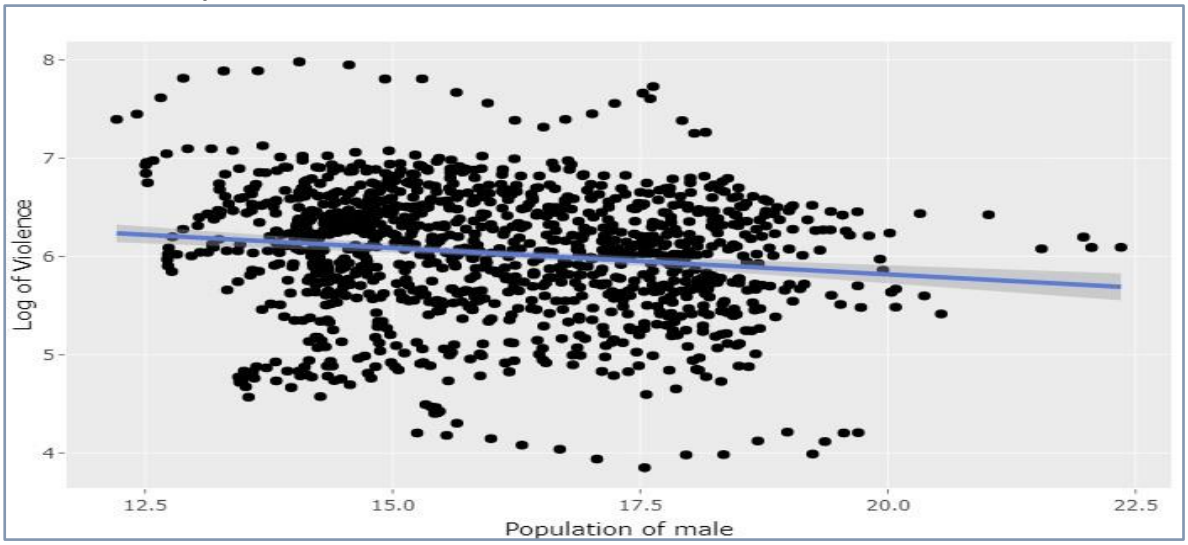
6) Male Population:



Case 1: States where the shall law was never implemented



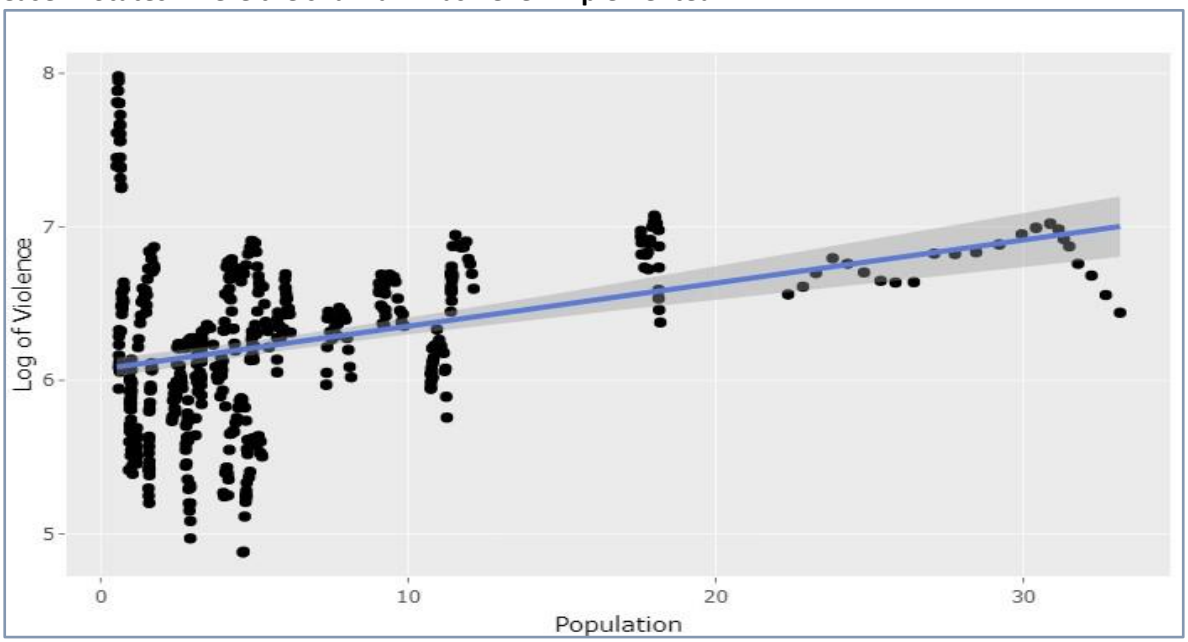
Case2: A scatter plot for all the states



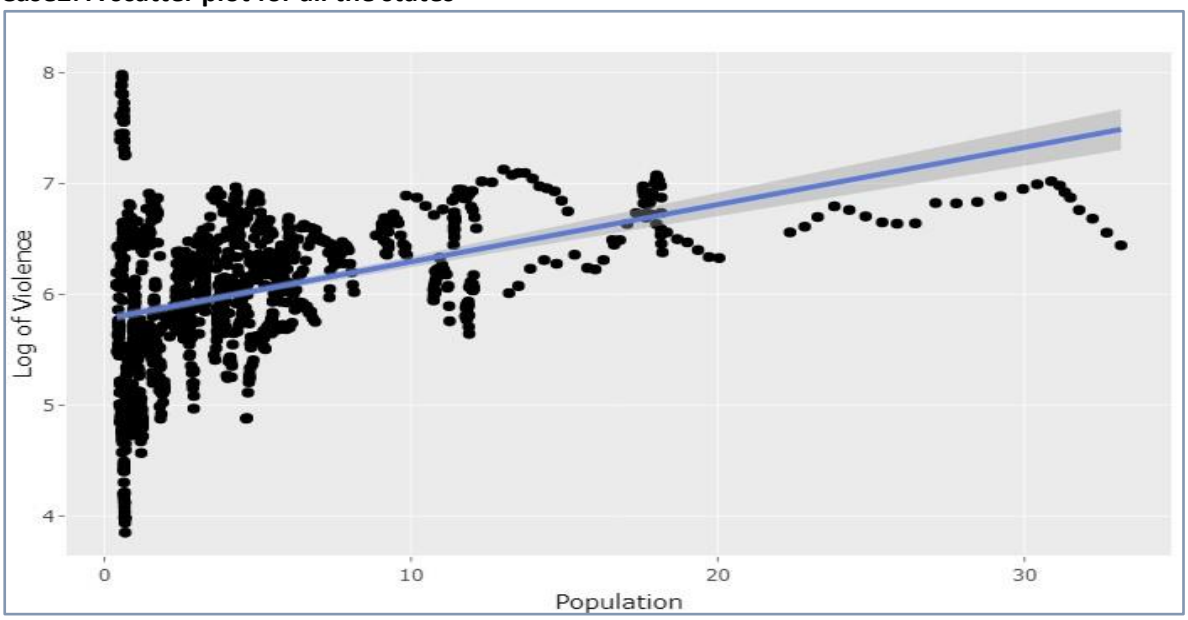
Observation: From the first graph we can observe that almost all the states have the similar young male population. From the 2nd and the 3rd graph, we can observe a downward trend, i.e. with the increase in young male population, we see a decrease in the violence crime rate.

7)Population:

Case 1: States where the shall law was never implemented



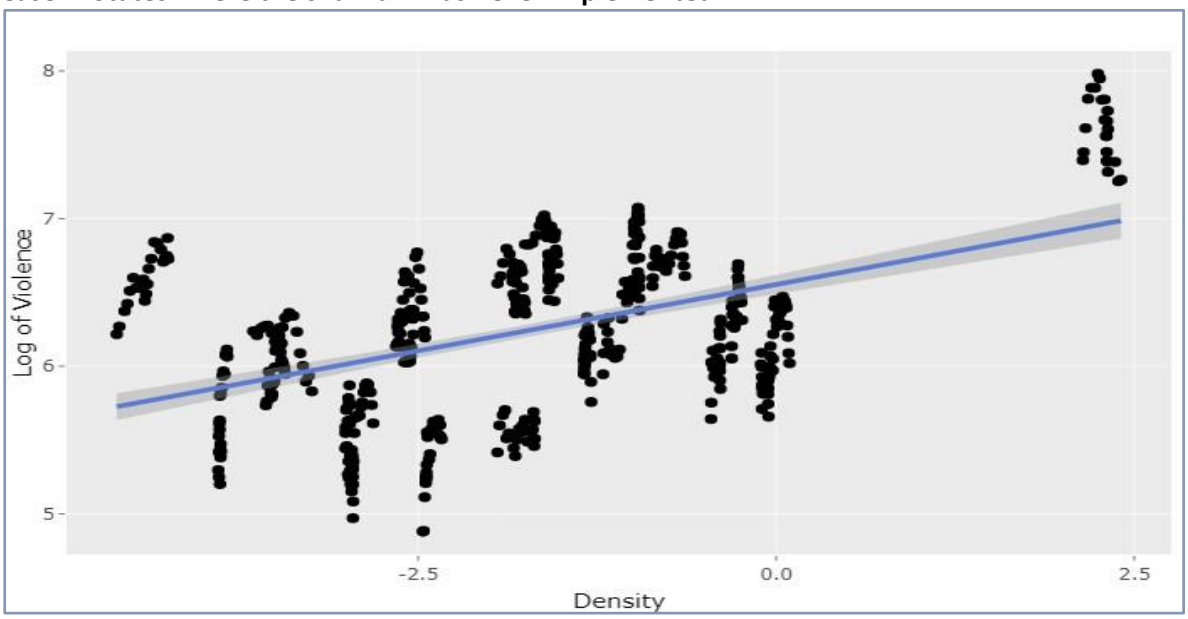
Case2: A scatter plot for all the states



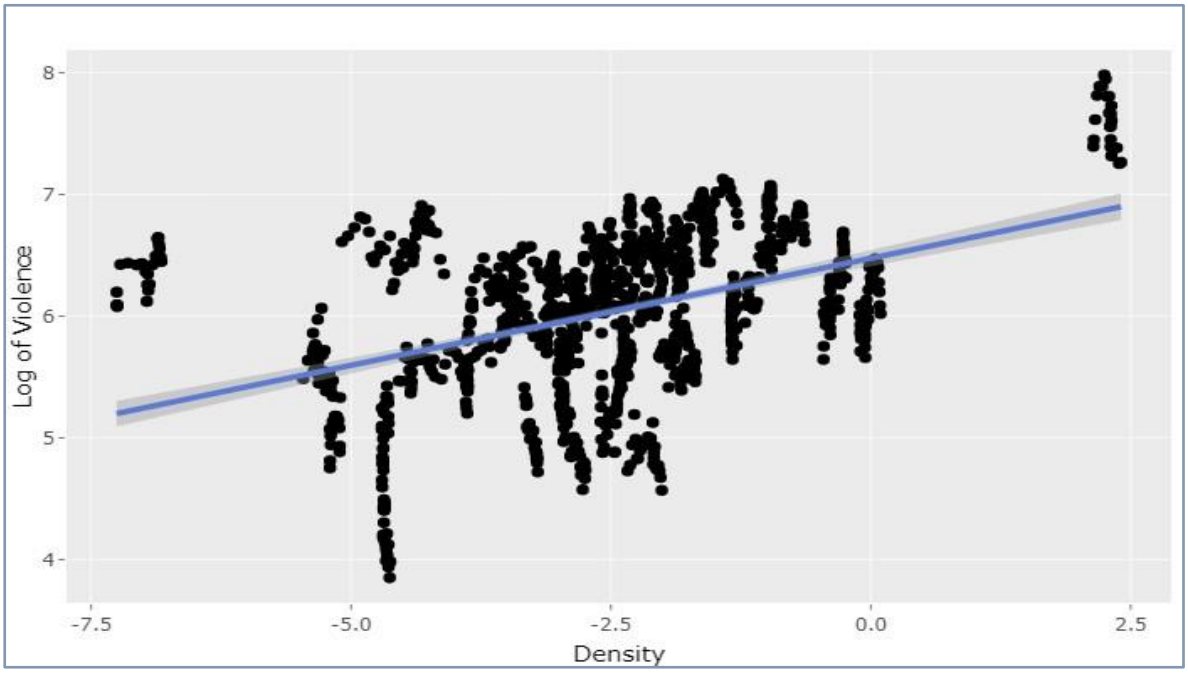
Observation: We can observe a positive relationship of population and violence crime late from the above two graphs.

8)Density

Case 1: States where the shall law was never implemented



Case2: A scatter plot for all the states



Observation: From both the graphs, we can see a positive relationship of density with the violence crime rate.

III. REGRESSION MODELS

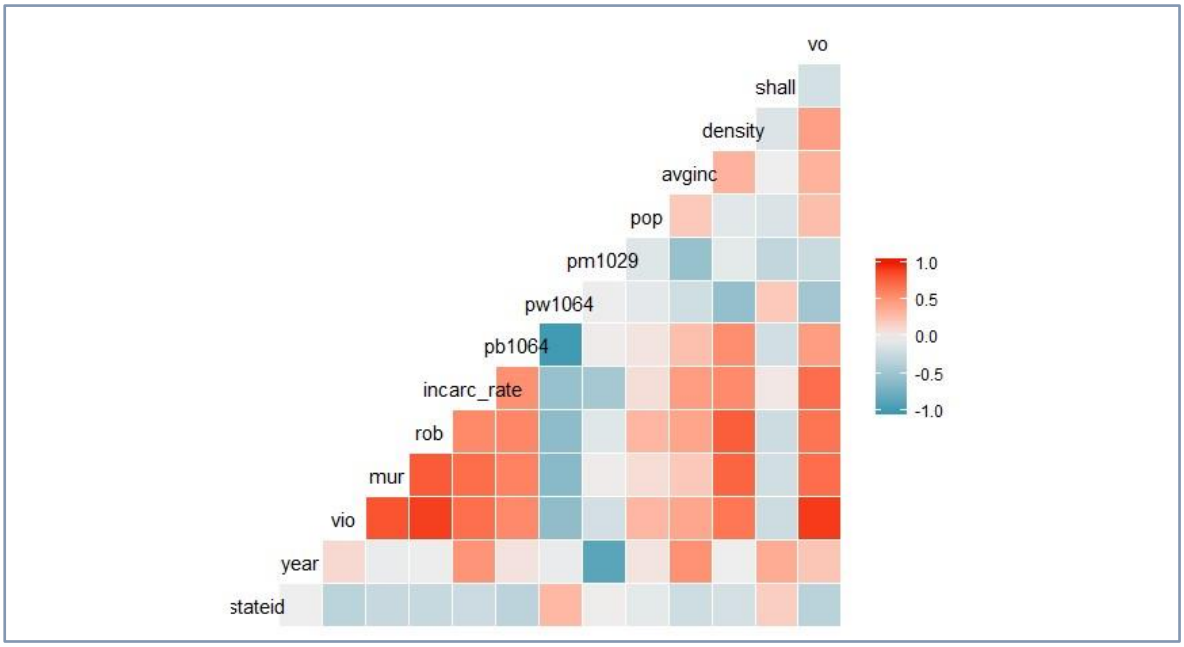
Based on our understanding of the dataset, we need to justify our choice of regression model. For a panel data, we can choose between a pooled OLS, random effects and fixed effects model. For all three models there are specific drawbacks and benefits. Our goal is to identify the effect of shall carry law on violent crime rate over time and across states.

Dependent Variable:

We will choose log of vio (violent crime rate) as our dependant variable. Our independent variables consist of shall, log(incarc_rate), log(density), avginc, pop, pm1029, pw1064 and pb1064.

Reason: [Link.] We found out that violence is a summation of murder, robbery, rape and assault. We assume that the same is applicable for our data set and are considering murder and robbery as a subset of Violence. Therefore, we take Violence as our dependent variable and remove murder and robbery from the dataset.

Correlation of Variables



Observation: We can observe that all the three variables, murder, robbery and violence crime rate are highly correlated with each other and show a similar relationship with the other independent variables. If the independent variables are highly correlated with each other. A bias is created and standard error portray a wrong picture. This is known as simultaneous causality bias in which both dependent and independent variables affect each other.

After removing murder and robbery from our dataset, we create a correlation matrix containing all the variables.

```
. pwcorr log_vio log_incarc_rate log_density shall avginc pop pm1029 pw1064 pb1064
```

	log_vio	log_in~e	log_de~y	shall	avginc	pop	pm1029
log_vio	1.0000						
log_incarc~e	0.6473	1.0000					
log_density	0.4282	0.2191	1.0000				
shall	-0.2943	0.0482	-0.1582	1.0000			
avginc	0.3629	0.4360	0.3846	-0.0000	1.0000		
pop	0.4194	0.1907	0.3414	-0.1244	0.2152	1.0000	
pm1029	-0.1437	-0.5445	-0.2377	-0.2772	-0.5279	-0.0975	1.0000
pw1064	-0.4716	-0.4606	-0.4241	0.2123	-0.1912	-0.0654	-0.0126
pb1064	0.4830	0.4776	0.4107	-0.1839	0.2627	0.0581	0.0162

	pw1064	pb1064
pw1064	1.0000	
pb1064	-0.9820	1.0000

.

Observation: Based on this correlation matrix, we see that pw1064 and pb1064 are highly negatively correlated. This could potentially lead to multicollinearity problems and that could undermine the significance of the variables. This is something to keep an eye on as we move forward with the models.

1. Pooled OLS

We first consider a pooled OLS model. Here the data on different states are simply pooled together without necessarily having provisions for differences between each state.

```
. xtset stateid year
       panel variable:  stateid (strongly balanced)
        time variable:  year, 77 to 99
                delta:  1 unit

. regress log_vio log_incarc_rate log_density shall avginc pop pm1029 pw1064 pb1064
```

Source	SS	df	MS		
Model	328.008468	8	41.0010585	Number of obs	= 1173
Residual	160.623091	1164	.137992346	F(8, 1164)	= 297.13
				Prob > F	= 0.0000
				R-squared	= 0.6713
				Adj R-squared	= 0.6690
Total	488.631558	1172	.416921125	Root MSE	= .37147

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

Observations:

I. Based on this model, the presence of the shall carry law brings the violent crime rate down by approximately 28%. This seems inflated due to combining all individual effects.

II. All variables other than pw1064 and pb1064 are significant in explaining how violent crime rate is affected.

III. Male population causes a 12% increase in violent crime rate with an increase of one percent. A 1% increase in incarceration rate and density leads to an increase in violent crime rate by 0.69% and 0.09% respectively

Test for Significance: We run a joint significance test for the variables pw1064 and pb1064 and obtained the following result. Based on the same we can confirm that neither of these variables are able to significantly affect violent crime rate.

```
. test pw1064 pb1064

 ( 1)  pw1064 = 0
 ( 2)  pb1064 = 0

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

Test for heteroskedasticity: Regression without the insignificant variables and with robust standard errors. The results obtained are as follows:

I. There is no significant evidence for heteroskedasticity with a p value of 0.0027
II. We see that shall carry law reduces violent crime rate by 28% and we have significant coefficients

```
. regress log_vio log_incarc_rate log_density shall avginc pop pm1029, robust

Linear regression                               Number of obs =    1173
                                                F(  6,  1166) =  389.89
                                                Prob > F      =  0.0000
                                                R-squared     =  0.6709
                                                Root MSE      =  .37137
```

log_vio	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_incarc_rate	.6781481	.0191451	35.42	0.000	.6405855	.7157108
log_density	.0880118	.0075957	11.59	0.000	.073109	.1029146
shall	-.2780539	.0282393	-9.85	0.000	-.3334594	-.2226483
avginc	.0239844	.0050571	4.74	0.000	.0140623	.0339064
pop	.0245819	.0024664	9.97	0.000	.0197428	.0294211
pm1029	.1134168	.0080454	14.10	0.000	.0976317	.1292019
_cons	.5193309	.2162536	2.40	0.016	.0950413	.9436206

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: fitted values of log_vio

        chi2(1)      =     8.97
        Prob > chi2  =   0.0027
```

Drawback: As mentioned, the pooled OLS model could be overestimating the effect of shall carry law on violent crime rate. Certain time invariant omitted variables like demographics and cultural attitude of population could be causing this effect. To guard against this bias, we use a fixed effects model.

2. Entity Fixed Effects

The pooled model had a crude assumption that all states have the same coefficients. This is an assumption that is relaxed in the fixed effects model and we bring some individual heterogeneity. This is captured by the intercept which is individual specific.

```
Fixed-effects (within) regression               Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.2236                         Obs per group: min =        23
       between = 0.1068                                        avg =      23.0
       overall = 0.0757                                        max =        23

                                                F(8,1114)          =     40.11
corr(u_i, Xb)  = -0.6657                        Prob > F           =    0.0000
```

log_vio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_incarc_rate	-.0672299	.0282092	-2.38	0.017	-.122579	-.0118808
log_density	-.251832	.0859535	-2.93	0.003	-.420481	-.0831831
shall	-.0379066	.0189886	-2.00	0.046	-.075164	-.0006491
avginc	-.0041476	.0057273	-0.72	0.469	-.0153851	.0070899
pop	.024386	.0092824	2.63	0.009	.0061732	.0425989
pm1029	-.0690675	.0083143	-8.31	0.000	-.0853809	-.052754
pw1064	.0428067	.0052073	8.22	0.000	.0325894	.053024
pb1064	.0952893	.0150322	6.34	0.000	.0657947	.1247839
_cons	3.592115	.4393088	8.18	0.000	2.730149	4.454081
sigma_u	.81282483					
sigma_e	.16012284					
rho	.96264251	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(50, 1114) =    103.01                     Prob > F = 0.0000
```

Observations:

I. The presence of shall carry law brings down violent crime rate by 3.7% overtime compared to when it is not present in a state
II. All variables other than average income are at 5% in affecting violent crime rate.
III. Pm1029 has an unexpected negative coefficient as it brings down violent crime rate by 6.9% with an increase of one percent over time.
IV. Incarceration rate seemingly has the desired effect by reducing violent crime rate by 0.067% for every 1% increase of its own

We re-estimate the model after dropping the average income variable. As expected, all variables are significant now and the shall carry law has a 3.8% effect on the violent crime rate.

```
Fixed-effects (within) regression               Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.2233                         Obs per group: min =        23
       between = 0.1087                                        avg =      23.0
       overall = 0.0771                                        max =        23

                                                F(7,1115)          =     45.78
corr(u_i, Xb)  = -0.6658                        Prob > F           =    0.0000
```

log_vio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_incarc_rate	-.0726068	.0272087	-2.67	0.008	-.1259928	-.0192209
log_density	-.2503523	.0859108	-2.91	0.004	-.4189175	-.0817872
shall	-.0380101	.018984	-2.00	0.046	-.0752585	-.0007617
pop	.0241646	.0092753	2.61	0.009	.0059655	.0423637
pm1029	-.0672519	.0079256	-8.49	0.000	-.0828028	-.0517011
pw1064	.0425889	.0051975	8.19	0.000	.0323908	.0527869
pb1064	.0940313	.0149283	6.30	0.000	.0647406	.123322
_cons	3.559252	.4368656	8.15	0.000	2.702081	4.416423
sigma_u	.81222128					
sigma_e	.16008869					
rho	.96260441	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(50, 1115) =    104.49                     Prob > F = 0.0000
```

Drawbacks: There are still possible drawbacks as fixed effects model can have problems with variables that are time invariant or slow moving. In order to correct this potential bias, we will add dummy variables for the time variable.

3. Time and Entity Fixed Effects

```
Fixed-effects (within) regression               Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.4255                         Obs per group: min =        23
       between = 0.2539                                        avg =      23.0
       overall = 0.1814                                        max =        23

                                                F(29,1093)         =     27.92
corr(u_i, Xb)  = -0.7956                        Prob > F           =    0.0000
```

log_vio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_incarc_rate	-.104334	.0281554	-3.71	0.000	-.1595788	-.0490893
log_density	-.2563097	.0763925	-3.36	0.001	-.4062023	-.1064172
shall	-.0288042	.0170906	-1.69	0.092	-.0623382	.0047298
pop	.005857	.0082851	0.71	0.480	-.0103996	.0221136
pm1029	.0801748	.0149116	5.38	0.000	.0509162	.1094335
pw1064	-.0019243	.0072882	-0.26	0.792	-.0162247	.0123761
pb1064	-.0130955	.019027	-0.69	0.491	-.050429	.0242381
year						
78	.0688136	.0277243	2.48	0.013	.0144147	.1232125
79	.1877998	.0283456	6.63	0.000	.1321819	.2434177
80	.249354	.0290952	8.57	0.000	.1922652	.3064427
81	.2580909	.0302212	8.54	0.000	.1987928	.317389
82	.2518348	.0324587	7.76	0.000	.1881463	.3155233
83	.2312016	.0352156	6.57	0.000	.1621037	.3002995
84	.2749803	.0380284	7.23	0.000	.2003634	.3495972
85	.334481	.041	8.16	0.000	.2540334	.4149285
86	.4235679	.0444672	9.53	0.000	.3363171	.5108187
87	.4333483	.0481226	9.01	0.000	.3389251	.5277714
88	.5060538	.0519771	9.74	0.000	.4040677	.60804
89	.5721197	.0555931	10.29	0.000	.4630384	.681201
90	.7103155	.0673886	10.54	0.000	.5780898	.8425412
91	.7749214	.071368	10.86	0.000	.6348876	.9149551
92	.8186853	.0748359	10.94	0.000	.6718471	.9655235
93	.8511992	.0778462	10.93	0.000	.6984542	1.003944
94	.8481078	.0809506	10.48	0.000	.6892716	1.006944
95	.8546609	.084193	10.15	0.000	.6894627	1.019859
96	.8111687	.0871196	9.31	0.000	.6402282	.9821092
97	.8013464	.0895338	8.95	0.000	.6256688	.977024
98	.757431	.0918091	8.25	0.000	.577289	.9375731
99	.7087832	.0942369	7.52	0.000	.5238776	.8936888
_cons	4.287925	.465536	9.21	0.000	3.37448	5.20137

sigma_u	.94734974	
sigma_e	.13905185	
rho	.97891005	(fraction of variance due to u_i)

```
F test that all u_i=0:     F(50, 1093) =   128.32            Prob > F = 0.0000
```

Observations:

I. We see that the shall variable is just about significant at 10% alpha and reduces violent crime rate by 2.88%
II. All time variables are significant whereas pop, pw1064 and pb1064 are insignificant in explaining the changes to violent crime rate

After re-estimating the model without the insignificant variables, we see the same effect on the violent crime rate from the shall variable. Also, with increase in 1% of male population, violent crime rate increases by 7.6%.

```
Fixed-effects (within) regression               Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.4249                         Obs per group: min =        23
       between = 0.2467                                        avg =      23.0
       overall = 0.1701                                        max =        23

                                                F(26,1096)         =     31.15
corr(u_i, Xb)  = -0.7733                        Prob > F           =    0.0000
```

log_vio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_incarc_rate	-.1005002	.0276959	-3.63	0.000	-.1548432	-.0461572
log_density	-.2382381	.0663898	-3.59	0.000	-.3685035	-.1079727
shall	-.0288178	.0168153	-1.71	0.087	-.0618116	.004176
pm1029	.0768889	.0108402	7.09	0.000	.0556191	.0981587
year						
78	.0676706	.0275996	2.45	0.014	.0135165	.1218246
79	.185452	.0279454	6.64	0.000	.1306195	.2402845
80	.2457236	.0283041	8.68	0.000	.1901873	.30126
81	.2535553	.0288559	8.79	0.000	.1969362	.3101743
82	.245901	.0303581	8.10	0.000	.1863344	.3054675
83	.2240372	.0324242	6.91	0.000	.1604167	.2876576
84	.2666658	.0344256	7.75	0.000	.1991183	.3342133
85	.3250987	.0366164	8.88	0.000	.2532525	.3969449
86	.4130719	.03936	10.49	0.000	.3358425	.4903013
85	.3250987	.0366164	8.88	0.000	.2532525	.3969449
86	.4130719	.03936	10.49	0.000	.3358425	.4903013
87	.4216201	.0421331	10.01	0.000	.3389495	.5042906
88	.4929663	.0449431	10.97	0.000	.404782	.5811507
89	.5577559	.0476295	11.71	0.000	.4643006	.6512113
90	.690794	.0509648	13.55	0.000	.5907945	.7907935
91	.7541244	.0538912	13.99	0.000	.6483827	.859866
92	.7966235	.0563387	14.14	0.000	.6860797	.9071674
93	.8280542	.0583617	14.19	0.000	.7135409	.9425675
94	.8238815	.0603801	13.64	0.000	.7054078	.9423552
95	.8292683	.0626734	13.23	0.000	.706295	.9522417
96	.7846344	.0647286	12.12	0.000	.6576285	.9116403
97	.7737903	.0662833	11.67	0.000	.6437339	.9038468
98	.7288026	.0675518	10.79	0.000	.5962573	.861348
99	.678991	.0686805	9.89	0.000	.5442308	.8137512
_cons	4.218825	.2777268	15.19	0.000	3.673889	4.763761
sigma_u	.91183917					
sigma_e	.13893702					
rho	.97731014	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(50, 1096) =   151.19            Prob > F = 0.0000

. estimates store timefixed
```

To judge between the significance of time and entity fixed effects model, we will use the F test for joint significance. With a p value of 0.00, we reject that the null hypothesis and conclude that the time variables are jointly significant. We will go ahead with the inclusion of time effects in our model.

```
 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,  1096) =   21.91
            Prob > F =    0.0000
```

Drawbacks: There are some drawbacks of the fixed effects model which enable us to seriously consider the random effects model. The random effects estimator can estimate the effects of variables that are individually time-invariant. The random effects model uses general least squares which gives a lower variance and more efficient results.

4. Random Effects

The key point about random effects is that it also assumes the intercept to capture the individual differences, but it considers the intercept to be random.

```
Random-effects GLS regression                   Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.2022                         Obs per group: min =        23
       between = 0.4310                                        avg =      23.0
       overall = 0.4087                                        max =        23

                                                Wald chi2(8)       =    338.47
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

log_vio	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_incarc_rate	.001109	.0283521	0.04	0.969	-.0544602	.0566781
log_density	.0611245	.030036	2.04	0.042	.002255	.1199939
shall	-.0688798	.0192294	-3.58	0.000	-.1065687	-.0311909
avginc	-.0062443	.0058167	-1.07	0.283	-.0176449	.0051562
pop	.021794	.0063425	3.44	0.001	.0093629	.034225
pm1029	-.0407458	.0080205	-5.08	0.000	-.0564657	-.0250259
pw1064	.0401063	.0052927	7.58	0.000	.0297327	.0504798
pb1064	.111766	.0129132	8.66	0.000	.0864566	.1370753
_cons	3.708989	.4113809	9.02	0.000	2.902697	4.515281
sigma_u	.29802919					
sigma_e	.16012284					
rho	.77599895	(fraction of variance due to u_i)				

Observations:

I. Here we have a higher effect on violent crime rate through the shall carry law as we see a 6.8% fall in violent crime rate for a state that uses the shall carry law
II. This larger effect compared to fixed effects can be explained by the fact that there are two insignificant variables, incarceration rate and average income
III. A joint significance test shows that they are insignificant with a p value of 0.5476

```
. test log_incarc_rate avginc

 ( 1)  log_incarc_rate = 0
 ( 2)  avginc = 0

           chi2(  2) =    1.20
         Prob > chi2 =    0.5476
```

We re-estimate the model without the insignificant variables. At this stage, we have one insignificant variable in log of density and shall carry law has a 5.9% effect on violent crime rate.

```
Random-effects GLS regression                   Number of obs      =      1173
Group variable: stateid                         Number of groups   =        51

R-sq:  within  = 0.2078                         Obs per group: min =        23
       between = 0.4252                                        avg =      23.0
       overall = 0.3908                                        max =        23

                                                Wald chi2(6)       =    316.57
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

log_vio	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
log_density	.0369337	.0412075	0.90	0.370	-.0438314	.1176988
shall	-.0596268	.0187883	-3.17	0.002	-.0964511	-.0228024
pop	.0156832	.0072823	2.15	0.031	.0014101	.0299563
pm1029	-.0392529	.0038419	-10.22	0.000	-.0467829	-.0317229
pw1064	.0391065	.0049876	7.84	0.000	.029331	.0488821
pb1064	.0993713	.0127115	7.82	0.000	.0744572	.1242854
_cons	3.699693	.3920307	9.44	0.000	2.931327	4.468059
sigma_u	.46613711					
sigma_e	.16052711					
rho	.89397795	(fraction of variance due to u_i)				

Drawback: The problem with using random effects here would be the fact that the data was not selected randomly at all! This also leads into the fact that there is possible endogeneity. For all the benefits of random effects over fixed effects, this is the one that pulls it back.

5. Final Model (Random Effects vs Fixed Effects)

To see whether it is appropriate to use the random effects model, we will use the Hausman test. The Hausman test compares the coefficients of the fixed and random effects model and judges the presence of endogeneity.

```
. estimates store random

. hausman fixed random, sigmamore
```

	Coefficients			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
log_density	-.2503523	.0369337	-.287286	.0768012
shall	-.0380101	-.0596268	.0216166	.0042345
pop	.0241646	.0156832	.0084814	.0059595
pm1029	-.0672519	-.0392529	-.027999	.0070634
pw1064	.0425889	.0391065	.0034823	.0017111
pb1064	.0940313	.0993713	-.00534	.0082333

```
                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(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                      =       39.69
            Prob>chi2 =      0.0000
```

Observation: Based on the chi2 value of 39.69 and p value of 0.00, we will choose the fixed effects estimator over the random effect's estimator. We can clearly see that endogeneity is a problem in Random Effects model.

IV. CONCLUSION

- Our final model i.e. the Time and Entity Fixed Effects model, suggests that over time the presence of shall carry law reduces the violent crime rate by 2.88%
- A rise in male population by 1% leads to an increase of 7.6% in violent crime rate
- With increase in Incarceration rate by 1%, violent crime rate increases by 0.10%
- A 1% increase in density leads to a 0.23% increase in the violence crime rate

V. LIMITATIONS

- There are some limitations with using the fixed effects model including the fact that it is just sensible to use this model when there is state data even though it provides inefficient results as the standard errors are inflated when using ordinary least squares
- It is also not the best at estimating variables that are time invariant or slow moving which is why we used time and entity fixed effects model as our best one
- Since we found out endogeneity problem, we could have suggested an Instrumental variable
- IV will lead to a biased but consistent estimate which would not be an issue for large datasets and might have given a better model

With the above observations, we can conclude that shall law has an impact in controlling the Violence crime rate in the US. However, we would like to seriously question whether a 2.88% decrease in violent crime rate is truly indicative that the shall carry law is an effective tool against gun crime. The staggering numbers involving gun violence over the last few years is probably proof enough to say otherwise.