ECONOMETRICS PROJECT REPORT

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INTRODUCTION

Do more Guns reduce Crime?

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

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

Problem to be Solved

Do shall-issues law reduce crime-or not?

Understanding the Features

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)

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

	year	vio	mur	rob	incarc_rate	pb1064	pw1064	pm1029	pop	avginc	density	stateid	shall
1	77	414.4	14.2	96.8	83	8.384873	55.12291	18.17441	3.780403	9.563148	0.0745524019	1	0
2	78	419.1	13.3	99.1	94	8.352101	55.14367	17.99408	3.831838	9.932000	0.0755667314	1	0
3	79	413.3	13.2	109.5	144	8.329575	55.13586	17.83934	3.866248	9.877028	0.0762453228	1	0
4	80	448.5	13.2	132.1	141	8.408386	54.91259	17.73420	3.900368	9.541428	0.0768288076	1	0
5	81	470.5	11.9	126.5	149	8.483435	54.92513	17.67372	3.918531	9.548351	0.0771865770	1	0
6	82	447.7	10.6	112.0	183	8.514000	54.89621	17.51052	3.925229	9.478919	0.0773185119	1	0
7	83	416.0	9.2	98.4	215	8.545608	54.83936	17.35089	3.934103	9.783000	0.0774933100	1	0
8	84	431.2	9.4	96.1	243	8.559511	54.77876	17.11902	3.951826	10.357200	0.0778424144	1	0
9	85	457.5	9.8	105.4	256	8.562801	54.67899	16.85875	3.972520	10.725858	0.0782500431	1	0
10	86	558.0	10.1	111.6	267	8.566521	54.51791	16.57609	3.991562	11.091618	0.0786251277	1	0
11	87	559.2	9.3	112.2	283	8.592103	54.38770	16.28230	4.015257	11.323824	0.0790918767	1	0
12	88	558.6	9.9	117.8	307	8.618144	54.23505	15.99270	4.023848	11.654964	0.0792610943	1	0
13	89	590.8	10.2	133.9	300	8.638031	54.06622	15.67523	4.030224	11.963897	0.0793866888	1	0
14	90	708.6	11.6	143.7	328	8.699674	56.07016	15.38070	4.048508	12.063984	0.0797735602	1	0
15	91	844.2	11.5	152.8	370	8.771641	55.97353	15.18314	4.091025	12.087816	0.0806113258	1	0
16	92	871.7	11.0	164.9	394	8.877969	55.80952	15.02558	4.139269	12.398020	0.0815619528	1	0
17	93	780.4	11.6	159.5	407	8.972758	55.66076	14.86296	4.193114	12.395800	0.0826229304	1	0
18	94	683.7	11.9	171.2	431	9.047583	55.50783	14.67744	4.232965	12.673920	0.0834081769	1	0
19	95	632.4	11.2	185.8	450	9.094921	55.33187	14.54549	4.262731	12.872682	0.0839946941	1	0

Showing 1 to 20 of 1,173 entries, 13 total columns

The state names corresponding to each state Id are as follows:

State ID	*State Name*	*Abbreviation*	*State ID*	*State Name*	*Abbreviation*
1	Alabama	AK	30	Nebraska	NC
2	Alaska	AL	31	Nevada	ND
3	American Samoa	AS	32	New Hampshire	NE
4	Arizona	AR	33	New Jersey	NH
5	Arkansas	AZ	34	New Mexico	NJ
6	California	CA	35	New York	NM
7	Colorado	CO	36	North Carolina	NV
8	Connecticut	CT	37	North Dakota	NY
9	Delaware	DE	38	Northern Mariana Islands	MP
10	District of Columbia	DC	39	Ohio	OH
11	Florida	FL	40	Oklahoma	OK
12	Georgia	GA	41	Oregon	OR
13	Guam	GU	42	Pacific Trust Territory	
14	Hawaii	HI	43	Panama Canal Zone	
15	Idaho	IA	44	Pennsylvania	PA
16	Illinois	ID	45	Puerto Rico	PR
17	Indiana	IL	46	Rhode Island	RI
18	Iowa	IN	47	South Carolina	SC
19	Kansas	KS	48	South Dakota	SD
20	Kentucky	KY	49	Tennessee	TN
21	Louisiana	LA	50	Texas	TX
22	Maine	MA	51	U.S. Virgin Islands	US VI
23	Maryland	MD	52	Utah	UT
24	Massachusetts	ME	53	Vermont	VT
25	Michigan	MI	54	Virginia	VA
26	Minnesota	MN	55	Washington	WA
27	Mississippi	MO	56	West Virginia	WI
28	Missouri	MS	57	Wisconsin	WV
29	Montana	MT	58	Wyoming	WY

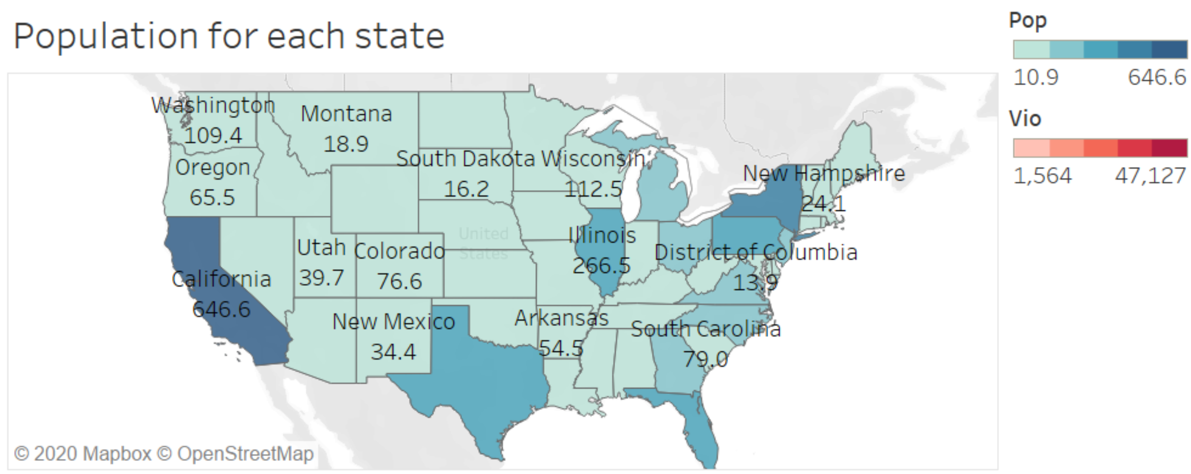
Expected impact of variables on violent crime(Based on Economic Theory)

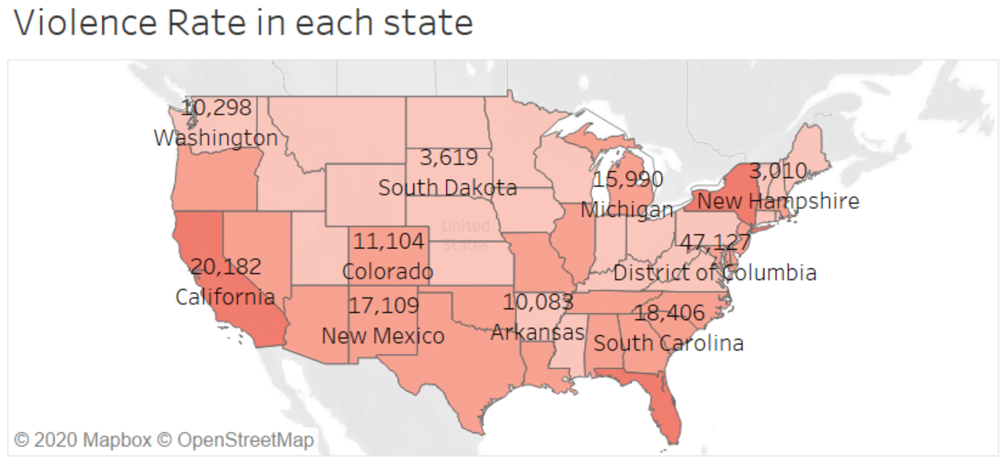
• SHALL: Introduction of Shall-carry law should reduce the crime rate and therefore will have an inverse relation with the crime rate.
• INCARC_RATE: Increase in Incarceration rate should reduce the crime rate and therefore will have an inverse relation with the crime rate.
• DENSITY: The role of population density in the generation or suppression of crime has been the subject of debate for decades. So, we can say that it can increase but it is uncertain.
• AVGINC: The real per capita personal income in the state should reduce the crime rate, therefore an inverse relation.
• POP: More the state population, more the chances violent crime rate. So, POP will have a positive relation with VIO.
•PM1029: Having more male population between ages 10 and 29 increase the chances of crime. Therefore, it will have positive relation with crime rate.
• PW1064 and PB1064: The effect of these two variables, according to economic theory, are highly contrasting. The difference because of different racial groups effect the crime rate differently and are debatable. The effect of population of blacks increase the crime rate as compared to population of whites. Competitive society in which there is an inequality in the distribution of goods, those groups with limited or restricted access to goods will be more likely to turn to crime.

OBSERVATIONS FROM DATA:

1. Population and Violent crime rate in each state

We have added state names column to the given data in order to increase our understanding of the data and used this column as a geographical representation in tableau.
From the visualisation we can observe that the states with high population are California, North Carolina followed by South Dakota and states with high violent crime rates are Florida, Georgia followed by California.
So we understand that the crimes are not significantly taking place in states having high population.





2. Murder rates in shall law issued states and non-issued states

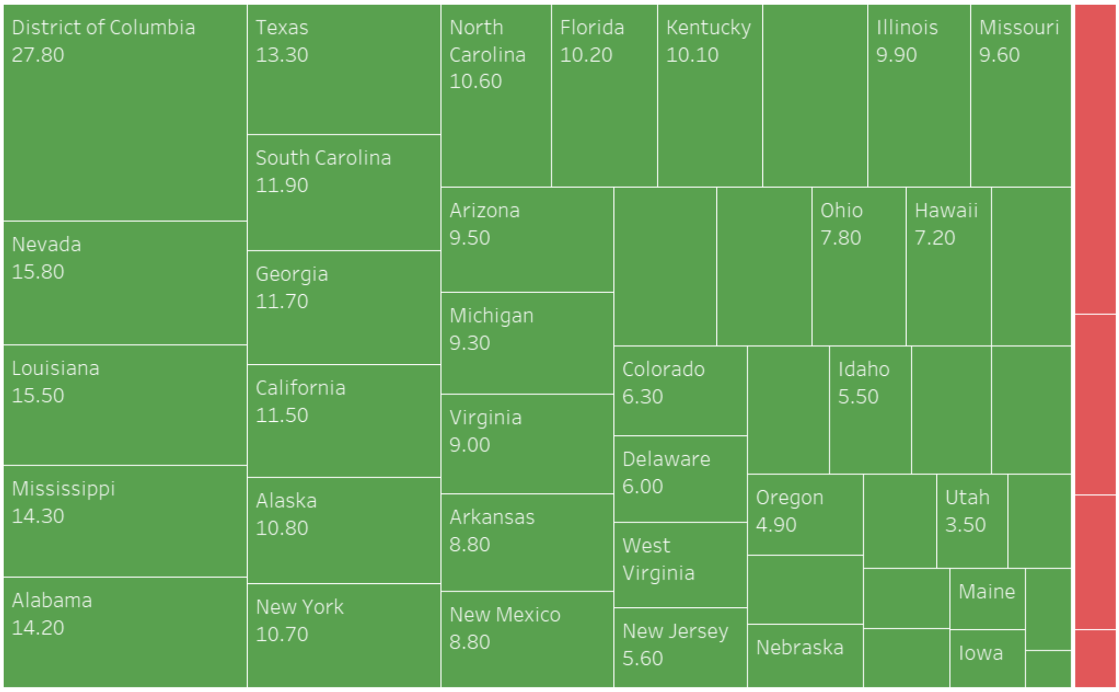
1977

In this visualisation we see that the number of states that have issued the shall-law (represented by brown colour) is less and the number of states that have not issued the law is high.

We observe that the state of District of Columbia has the highest murder rate

In accordance with our belief that issuing the shall law reduces crime, we can observe that the shall law issued states have less murder rate.

Murder rates in states

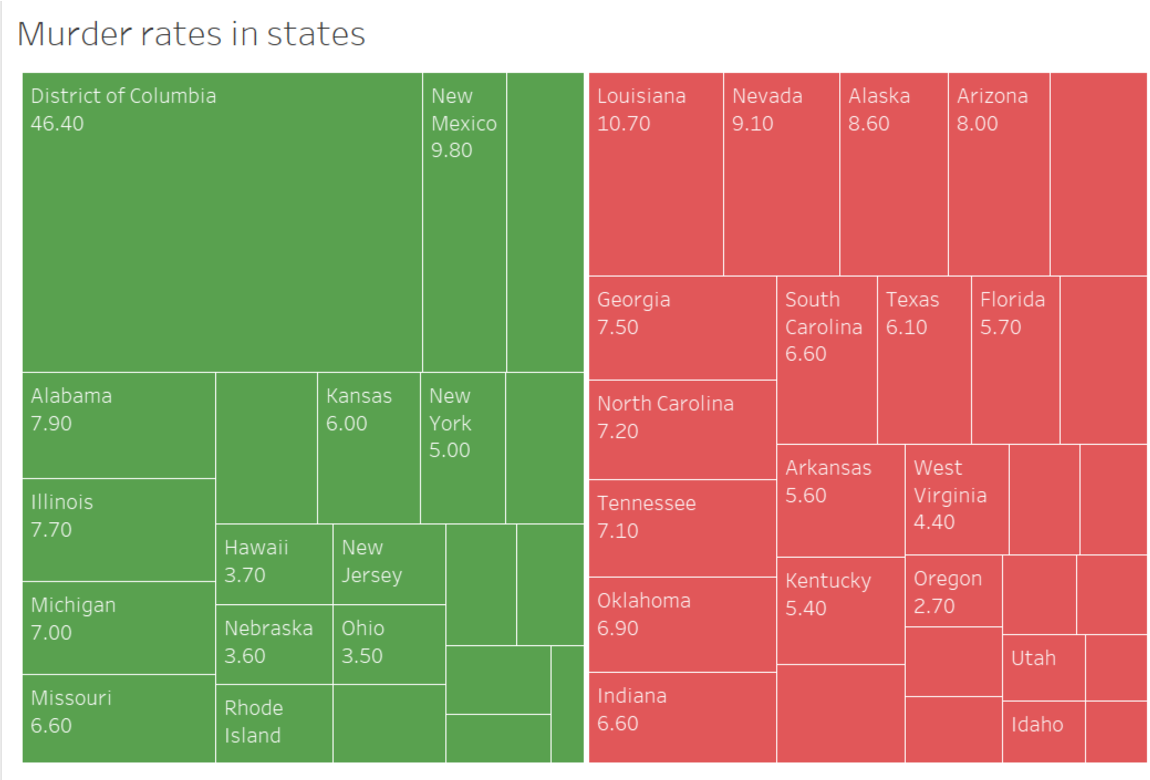


1999

This visualisation is the same as the above but for year 1999 when the shall law has been widely issued.

Here also the highest murder rate is in the state of District of Columbia and yet the law has not been issued for this state.

Almost half of all the states have got the law and for instance we can look at Georgia where previously in the year of 1977 the murder rate was around 11.7 and has reduced to half which is 7.50 after the shall law was issued.



3. Robbery rates in shall law issued states and non issued states

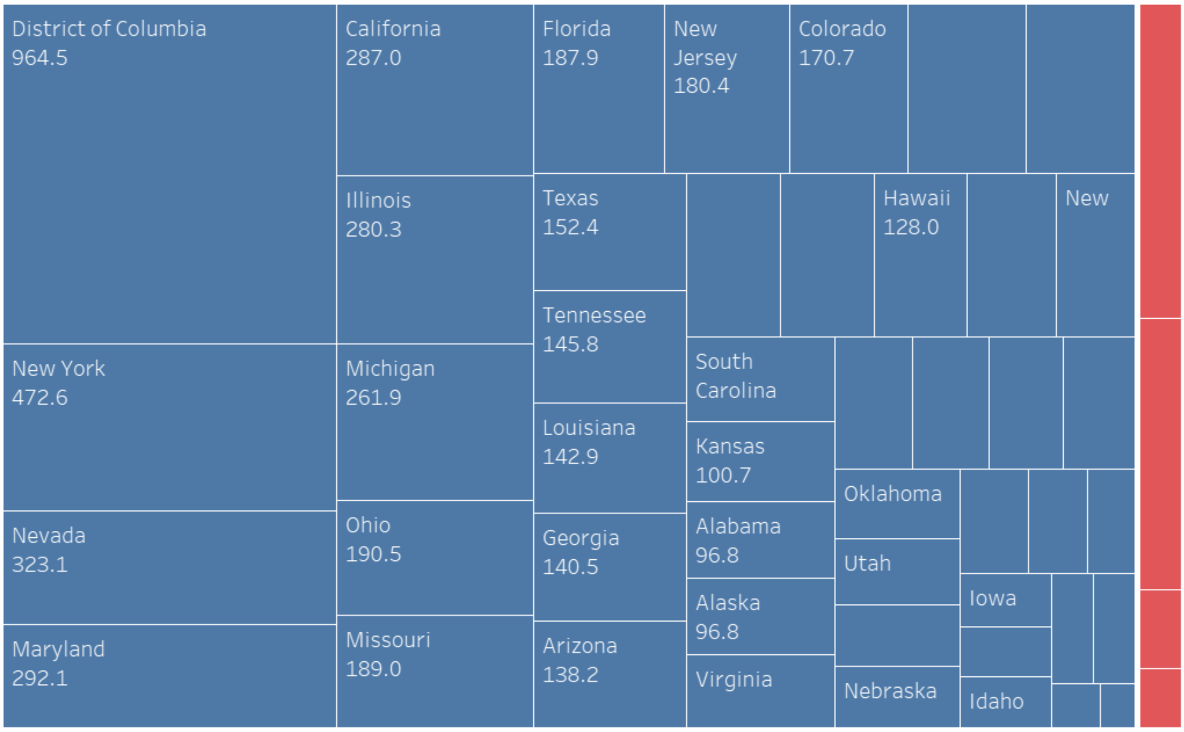
1977

Similar to the previous visualisations, now let us look at the robbery rates before and after shall law was issued.

In 1977 we see that District of Columbia again has the highest robbery rate of a high value(964.5).

We see that only 4 of the 51 states have been issued the shall law.

Robbery rates in each state



1999

Here again we see that District of Columbia has the highest robbery rate and the shall law was not issued through out.

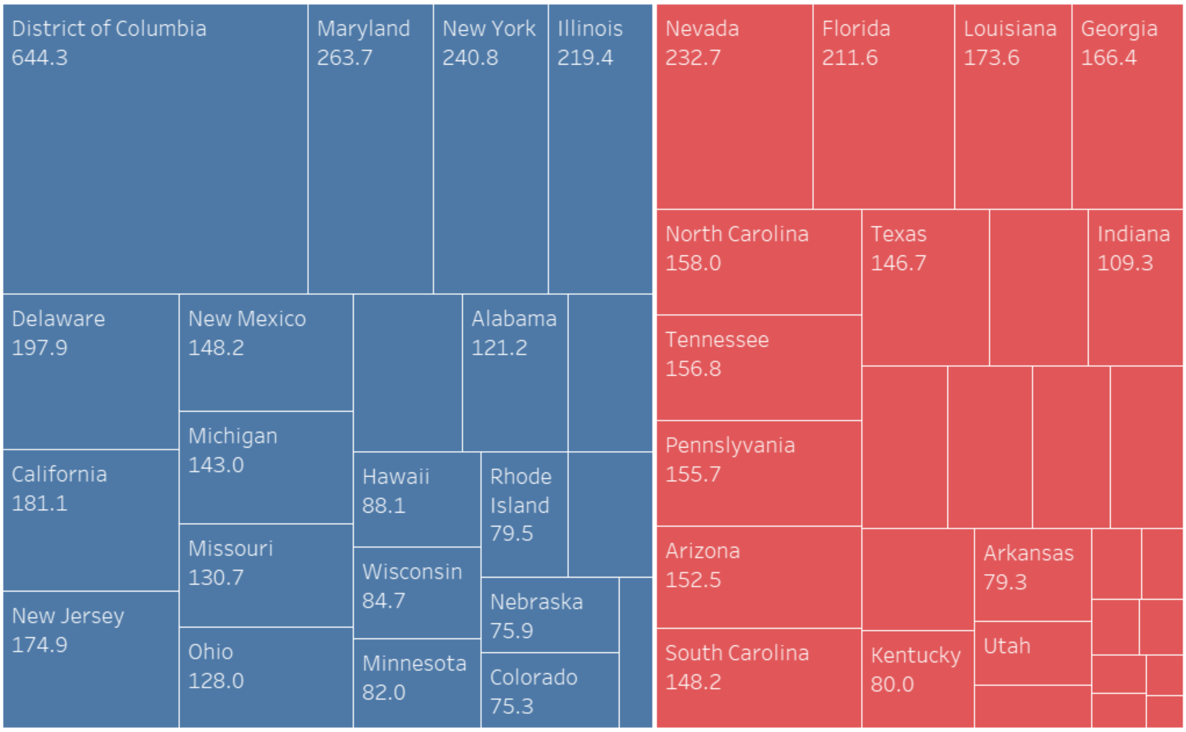
Let us look at the state of Nevada the rate has reduced from 323.1 to 232.7.

This justifies the statement that issuing the law reduced crime.

But at the same time when we look at countries like Florida the robbery rate has increased from 187.9 to 211.6 after the law was issued.

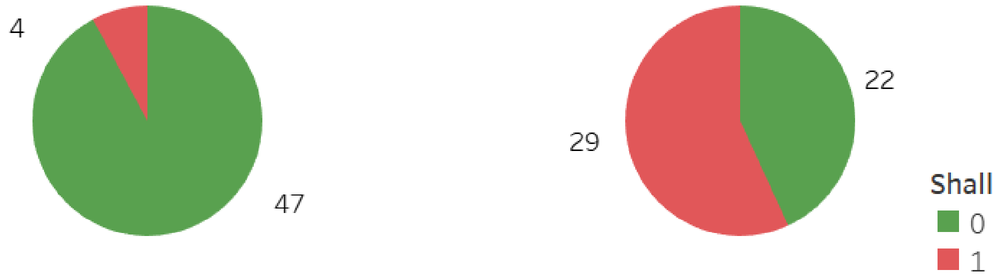
This is because people may tend to misuse such laws to make easy money.

Robbery rates in each state

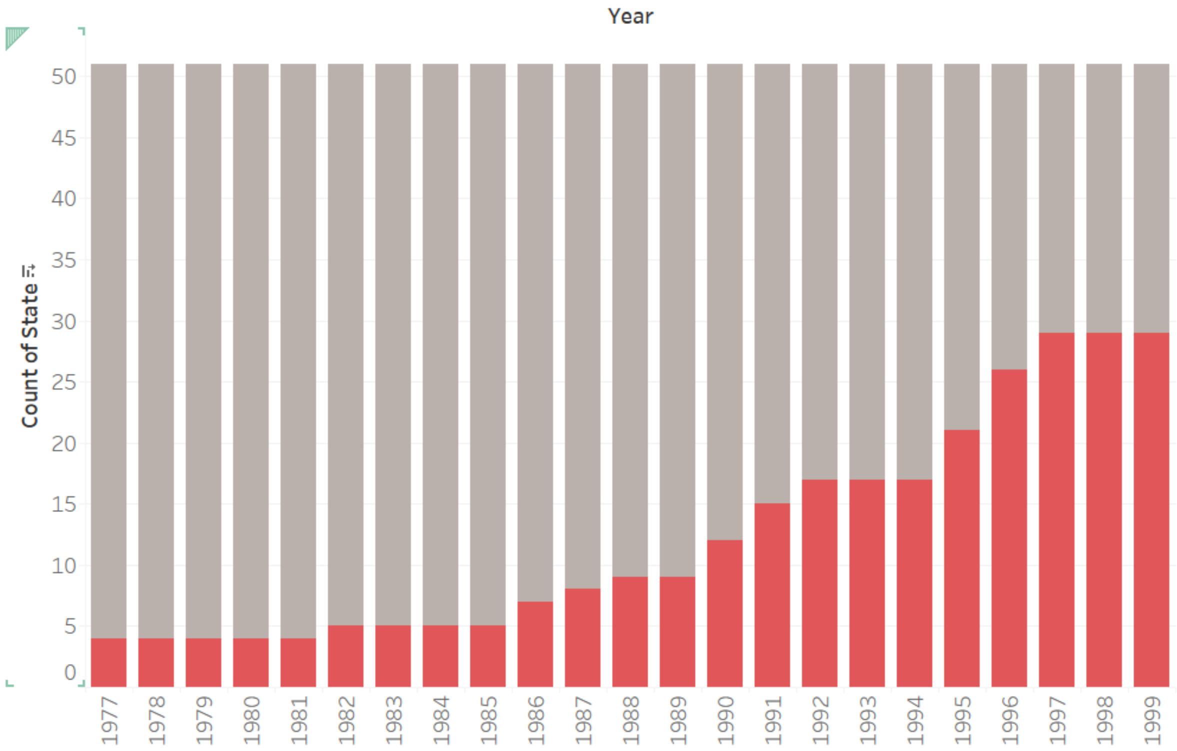


4. Shall law issued states over the years

From the pie charts below we clearly see that the number of states that have issued the shall law(red coloured) has increased from as low as 4 to 29 which is more than half of the total number of states.

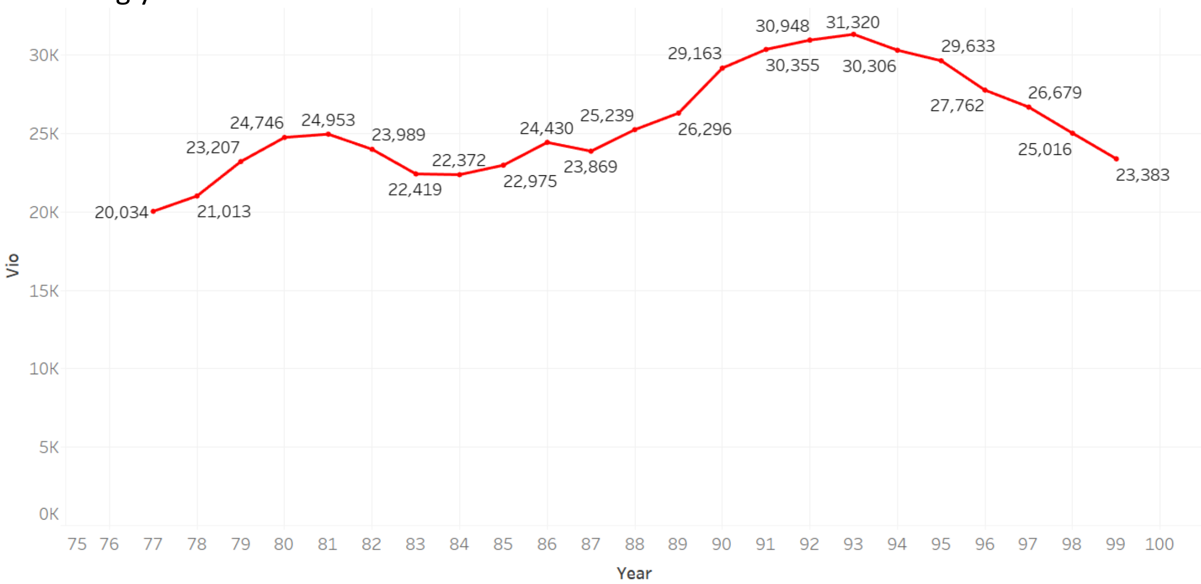


Now, let us look at this increase year by year.
We see that over the first ten years that is from 1977 to 1987 the increase of number of states that issued the law was slowly increasing.
But after the year 1987 and especially from year 1994 to 1997 we see a drastic peak.
Bill Clinton was the president of the USA during that time.



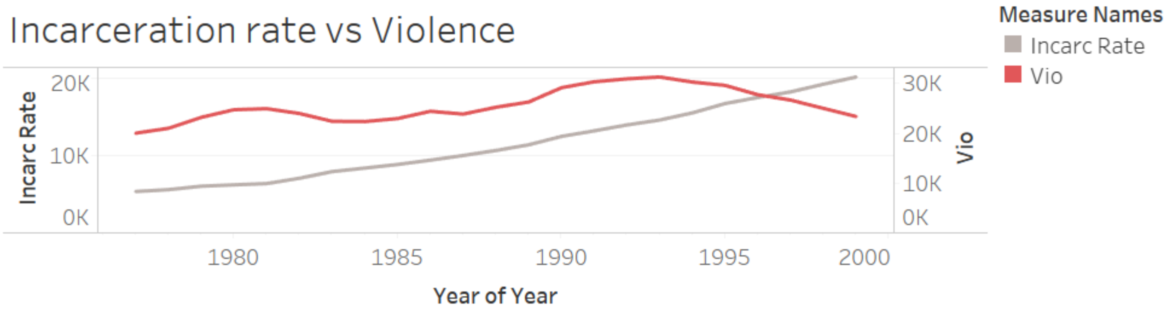
5. Violent crime rate over the years

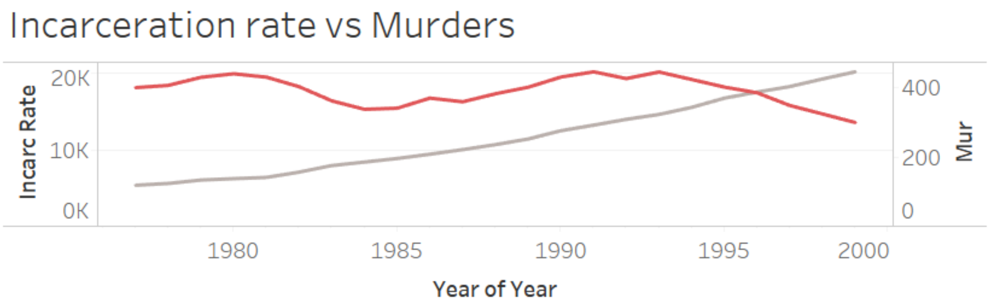
This graph shows the overall violent crime rates over the years from 1977 to 1999
The highest peak of crimes can be observed during the years 1992 to 1994 and then decreased as an inclined line.
This inclination is observed during the same period where the shall law has been issued increasingly.

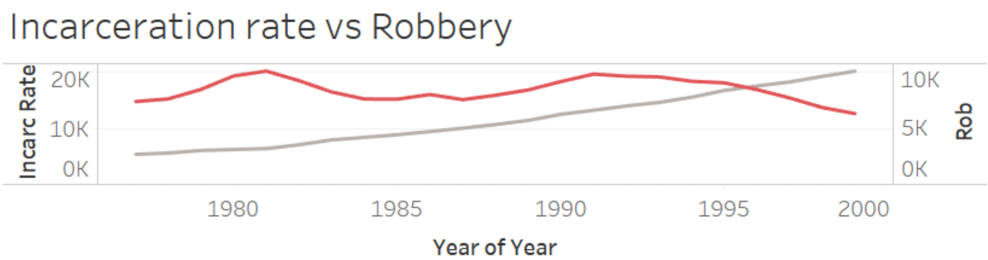


6. Has incarceration effected violent crimes?

Incarceration is the state of being confined in prison; imprisonment.
Imprisonment creates a kind of fear among people and we expect the crimes to reduce as the incarceration rate increases.
Let us look at the following graphs which show the incarceration rate along with violent crime rate, murder rate and robbery rate.





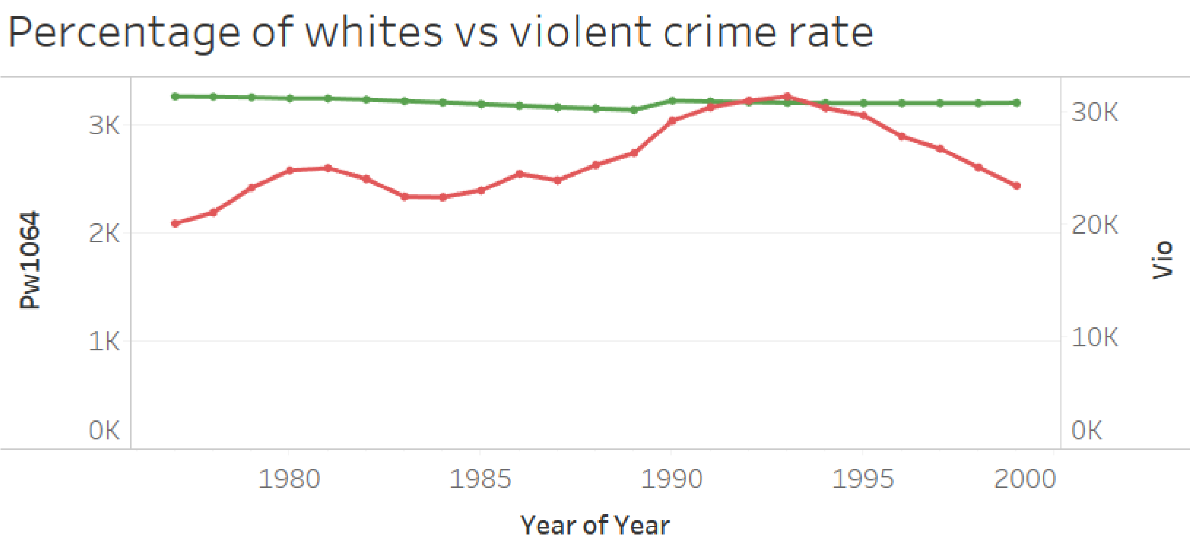


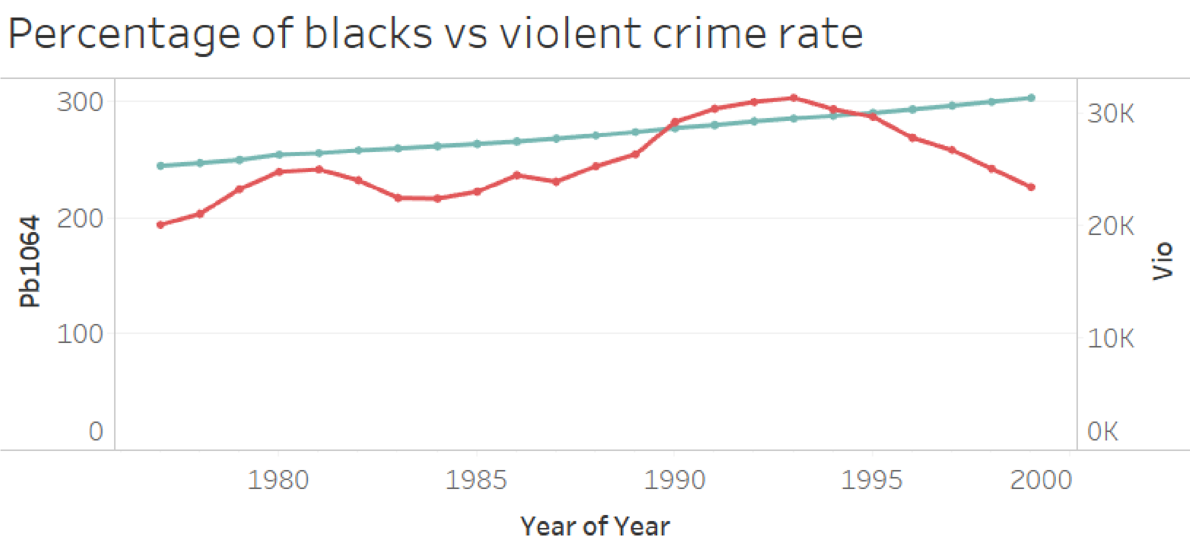
- As the incarceration rate increased over the years, the violent crime rate has not decreased until the year of 1995.
- Same is the case with murder rate but the robbery rate that has been steady over the years reduced after 1995 in the same fashion.

7. Whites vs blacks violence over years

-The effect of population of blacks increase the crime rate as compared to population of whites. Competitive society in which there is an inequality in the distribution of goods, those groups with limited or restricted access to goods will be more likely to turn to crime.
- In the below graph we observe that the percentage of whites of ages between 10 to 64 has been constant represented by the green line and the crime rate has seen some ups and downs.
-But the percentage of blacks of ages between 10 to 64 has increased slowly and the crime rate has seen ups and downs.

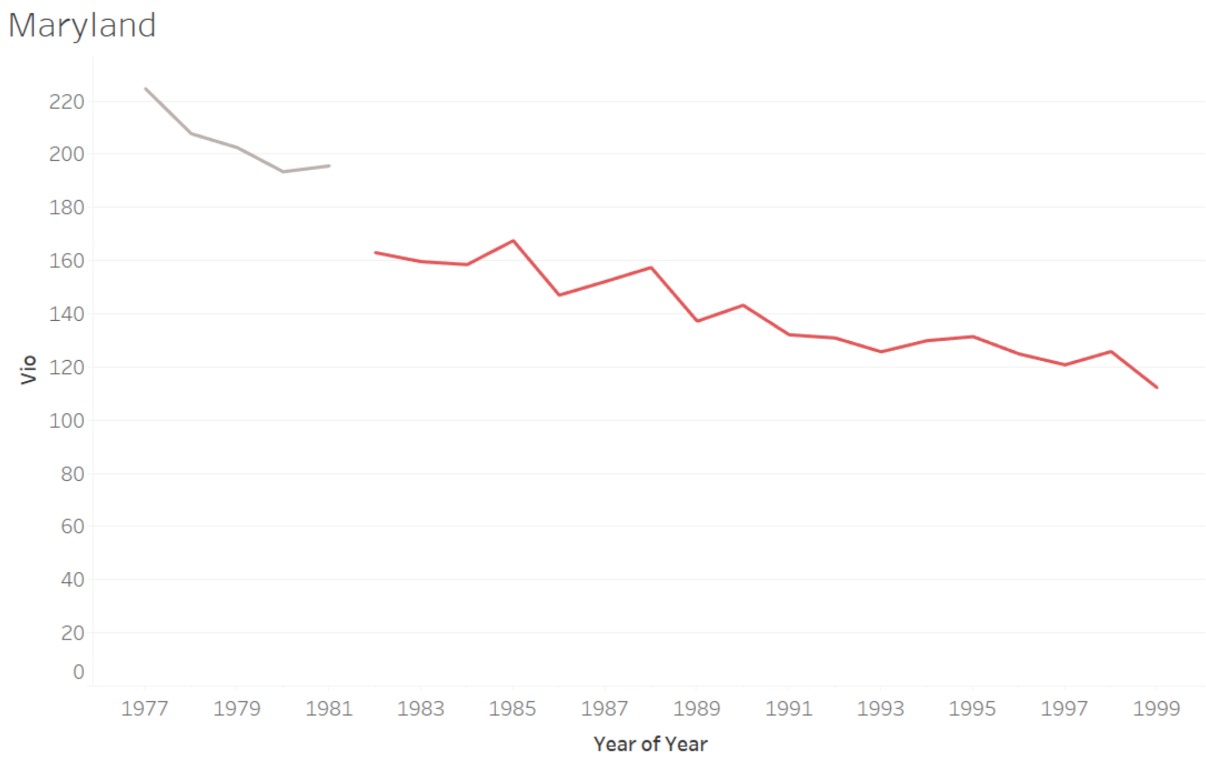
-From these visualisations we can't confirm that increase in percentage of blacks increases crime rates.





8. Crimes before and after shall law was issued

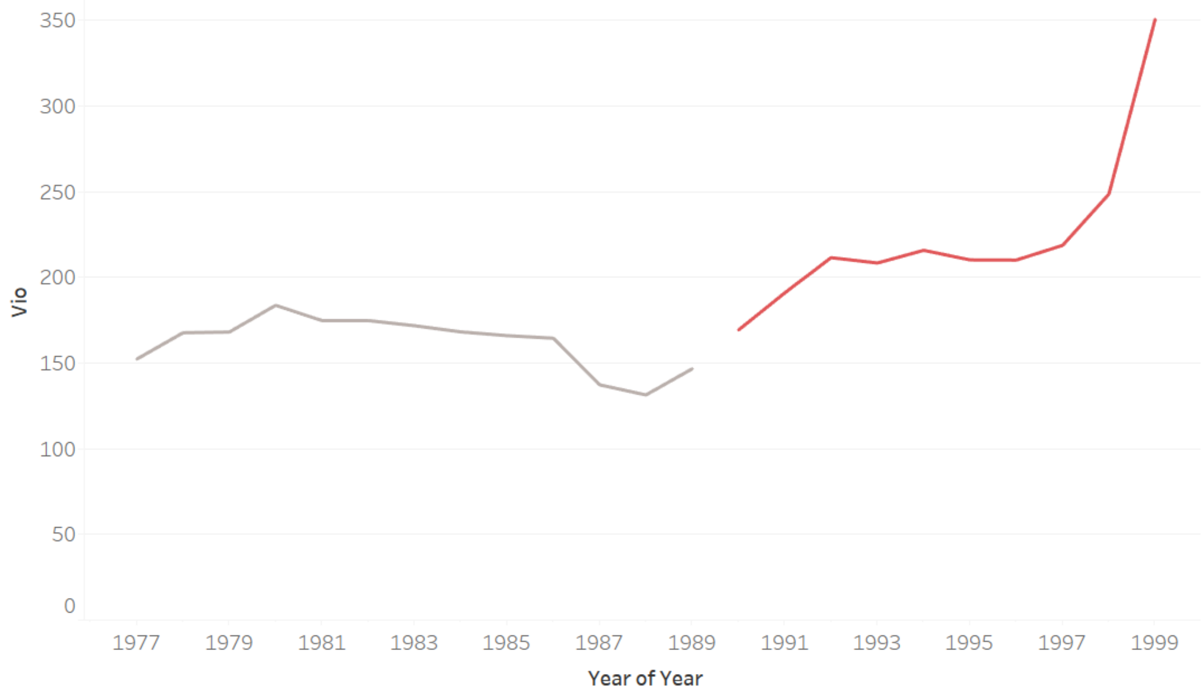
We believe that the crime rates have been reduced after the issuance of shall law. This is explained by states like Maryland.
In the below graph grey line indicates the violent crime rate when the state has not issued the law and red line indicates violent crime rate after the state issued the shall law.
We clearly see the decrease in crimes after the law has been issued(in this case after 1981).



But In some other states like Virginia which is shown below the violent crime rate has increased after the shall law has been issued.

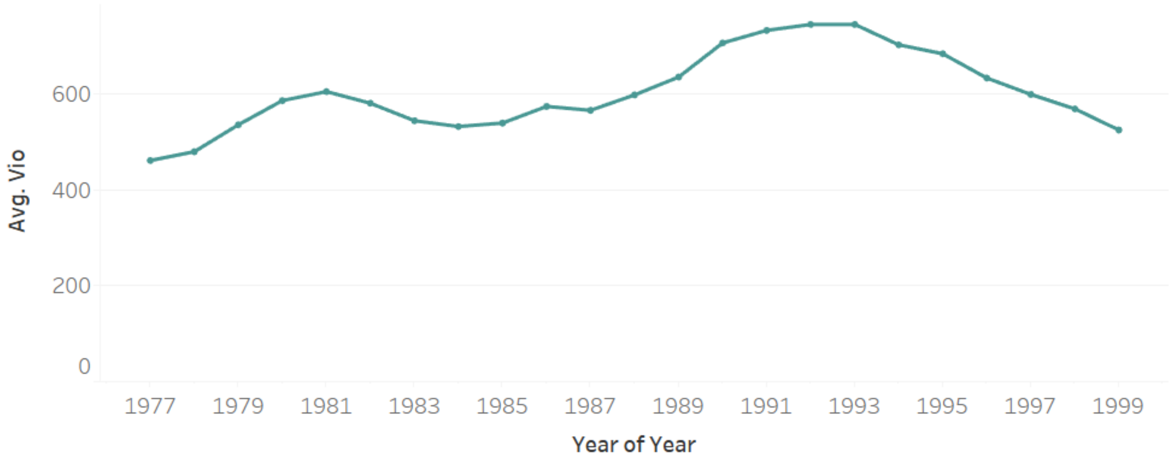
What fascinates us is the fact that there are other states like Virginia which include Nebraska, Rhode Island, Tennessee, etc.

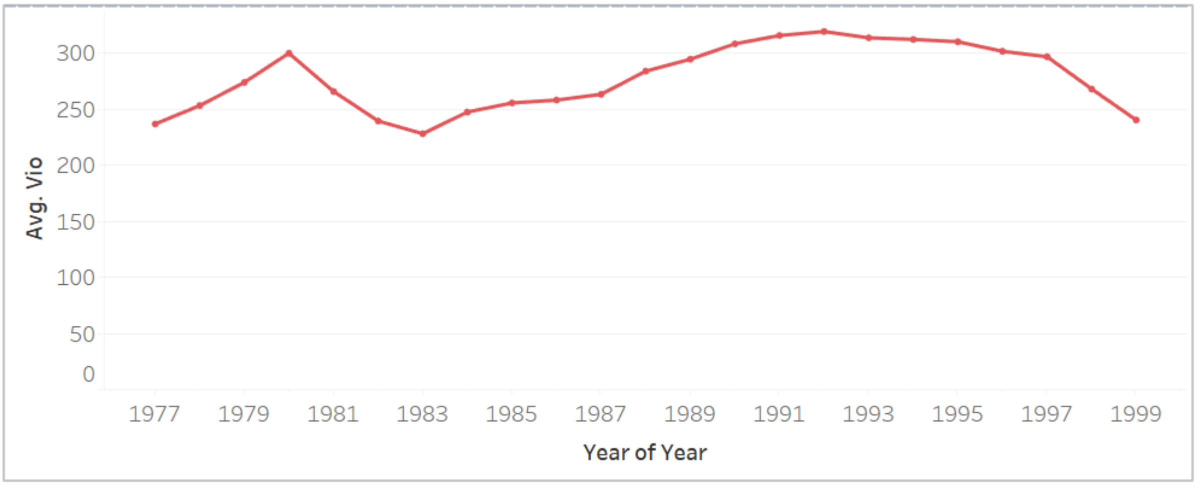
This can be because of other factors affecting the crime rate and there may be an interaction effect that is acting up to give such results.



9. States with vs without shall law from the beginning(1977)

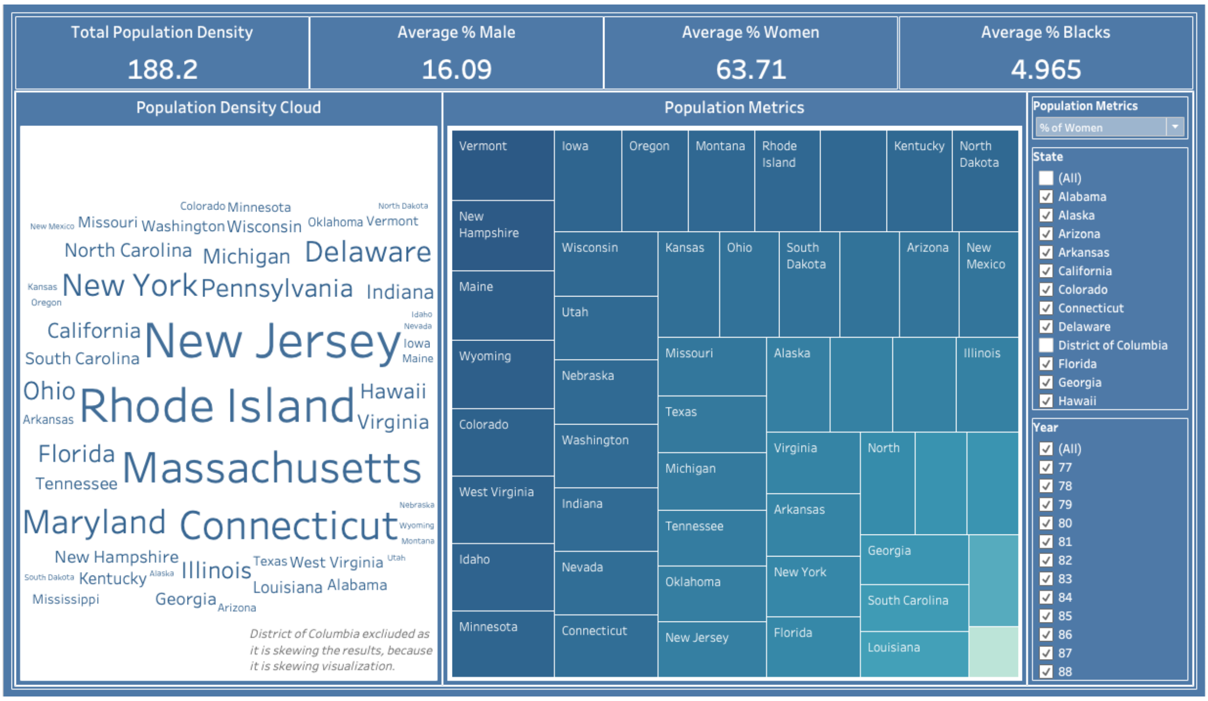
There are some states in which the law has not been issued from the beginning(1977) till 1999.
Let us look at the average violent crime rates(blue line) in those states.
These states include: Alabama, California, Connecticut, etc.
We see the crime rate does not show an increase or decrease alone but definitely by 1999 we see that the crimes have reduced.





There are some other states where the law has been issued from the beginning itself.
We look at the average crime rates(red line) of these states.
These states include: Iowa, New Jersey, Texas and Vermont.
We observe that the crimes have increase gradually and then decreased.
Again this can be because of factors other than the law.

Overall Summary Statistics



UNDERSTANDING DATA

Based on analysis and intuition, our understanding and hypotheses of the data is as follows:

Shall-Issue Law & Crime Rate:

- Over the years, the number of states that implemented the *Shall-Issue* law has increased (from 4 to 29) which means there is a possibility that more states trust this law to be effective in bringing down the crime rate.
- Hence, we expect the *shall-law* variable to play a significant role in bringing down the crime rate like violence and murder.
- However, we feel that this might not be applicable to robbery since in general robbery, property crimes, theft and stealth are more associated with weapons like guns and is expected to increase when more people have access to them.

Incarceration & Crime Rate:

- Incarceration rate has always been increasing over the years. However, the crime rate is not perfectly negatively correlated with incarceration rate.
- Hence, it is hard to believe that incarceration rate has effectively brought down crime rate.
- In fact, we feel that incarceration rate increased because crime rate increased which could lead to a direct correlation.

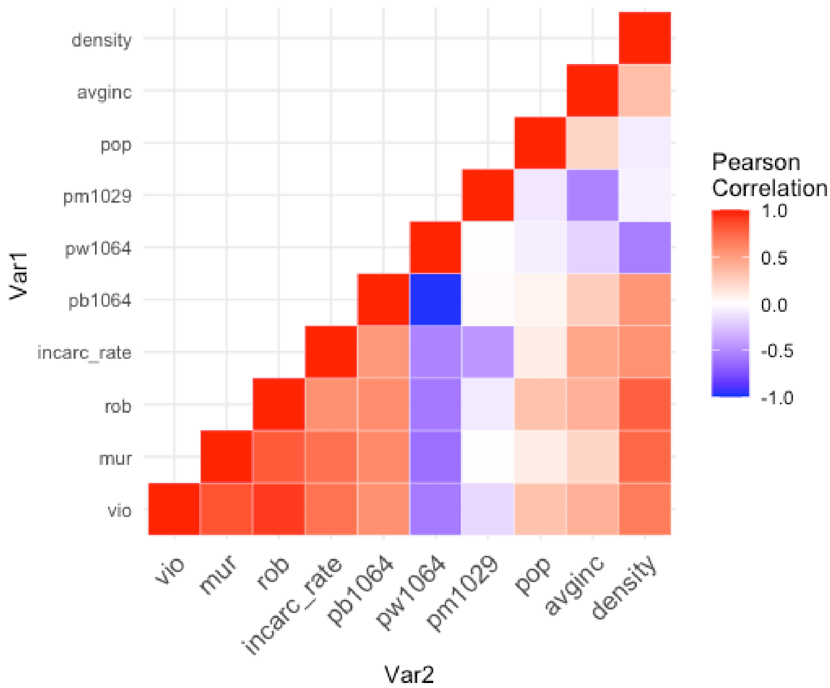
Population & Crime Rate:

- We intuit that population density is a key factor in explaining crime rate as it is common to expect more crime happening in more densely populated areas.

- The percentage of whites in any state is always higher than that of black and we don't find any meaningful relationship between race and crime rate or gender and crime rate.
- Thus, we expect *pm1029, pw1064* and *pb1064* variables to be less significant in explaining crime rate.

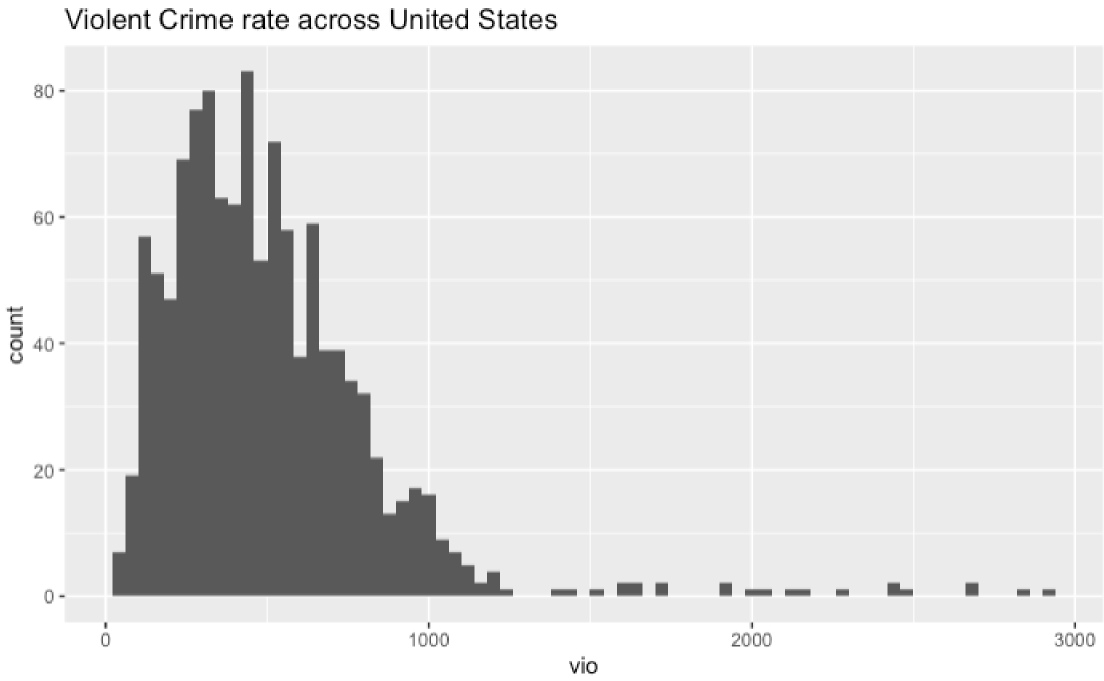
DESCRIPTIVE ANALYSIS

There are no missing values in the data

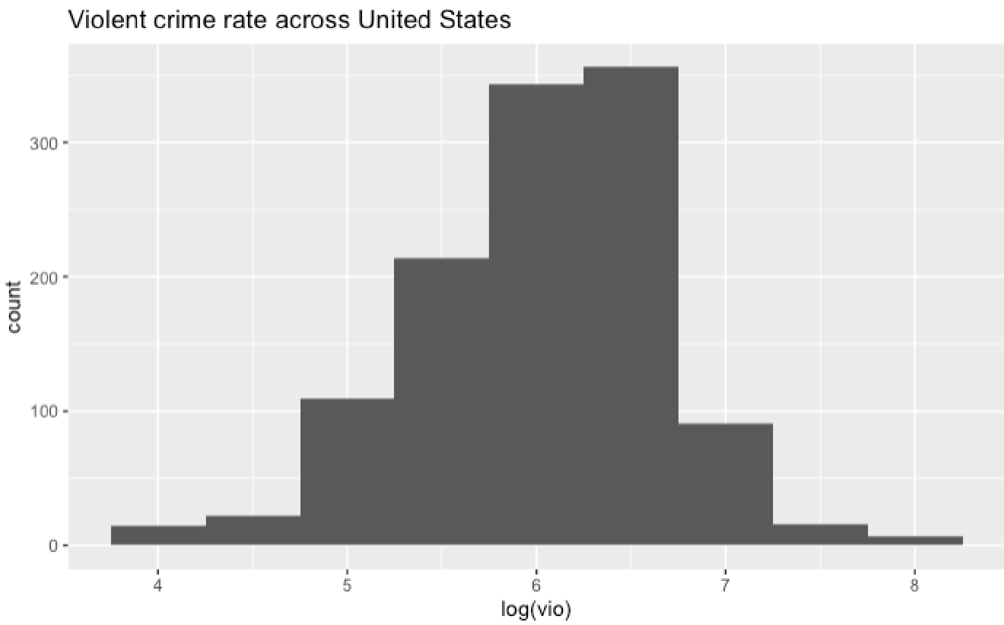


The heat map indicates that there is a high correlation between murder rate, crime rate and violent crimes.
We will use this information further in the analysis.
And we will estimate the result of shall law separately for violent crimes, murder rates and robbery rates.

Violent Crimes



Before applying log transformation, the distribution of crime rate across United States in heavily skewed towards right and positively skewed distribution. Most of the statistical analysis or statistical models require Normal Distribution because of its significant statistical properties such as constant mean and constant variance across the data. After applying necessary log transformation on data the distribution of crime rate became approximately symmetrical or at least weakly skewed but not heavily skewed.



OLS

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Call:
lm(formula = vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall, data = guns)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.53759 -0.19669  0.03829  0.21315  1.19112 

Coefficients:
              Estimate Std. Error t value             Pr(>|t|)    
(Intercept)  3.5499150  0.4360367   8.141 0.000000000000000999 ***
mur          0.0034401  0.0032353   1.063              0.28787    
rob          0.0031608  0.0001437  21.997 < 0.0000000000000002 ***
incarc_rate  0.0012571  0.0001126  11.161 < 0.0000000000000002 ***
pb1064       0.0578545  0.0133718   4.327 0.000016443642004075 ***
pw1064       0.0265646  0.0067147   3.956 0.000080767635351566 ***
pm1029      -0.0056762  0.0091565  -0.620              0.53544    
pop          0.0074291  0.0024851   2.989              0.00285 ** 
avginc      -0.0084354  0.0063823  -1.322              0.18653    
density     -0.2481097  0.0151810 -16.343 < 0.0000000000000002 ***
shall       -0.2779262  0.0263605 -10.543 < 0.0000000000000002 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3425 on 1162 degrees of freedom
Multiple R-squared:  0.721,	Adjusted R-squared:  0.7186 
F-statistic: 300.4 on 10 and 1162 DF,  p-value: < 0.00000000000000022
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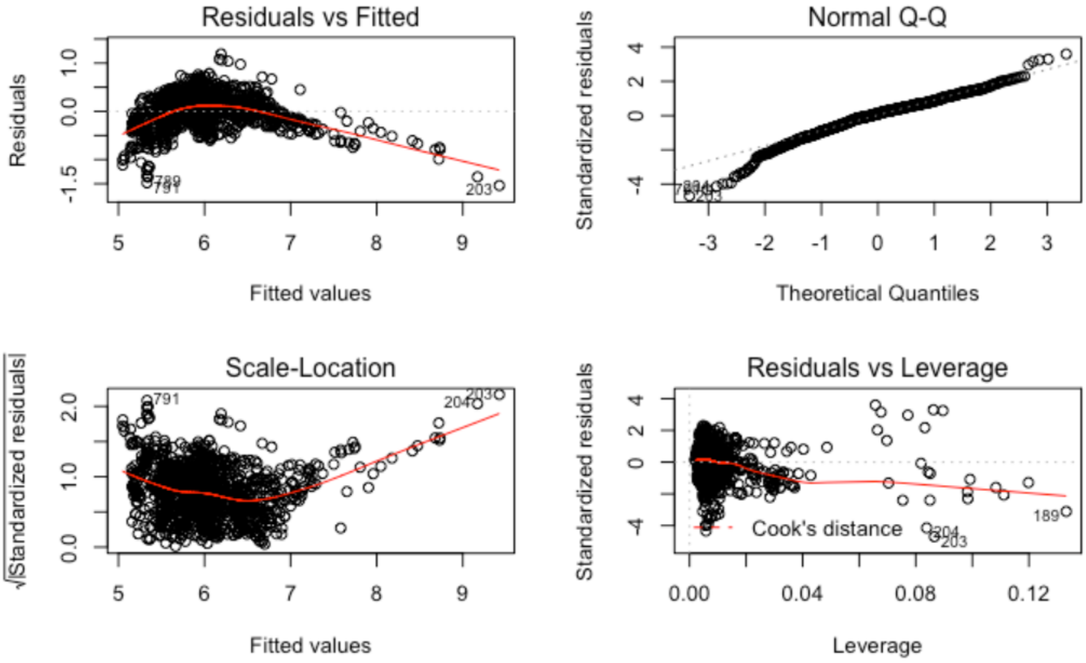
Interpretation

We have run our OLS regression with dependent variable as vio (Violent Crime) and independent variable as rest of the features.
From the results we can see that R squared is 0.721 and R squared is responsible for variation explained. Our model is able to explain 72.1% of variation in the data with all the explanatory variables included in that.
If the shall is passed then there will be 27.79% reduction in crime, which is quite high as a outcome for a law being passed and maybe this is an overestimation and can be an indication of bias.

Residual Graphs

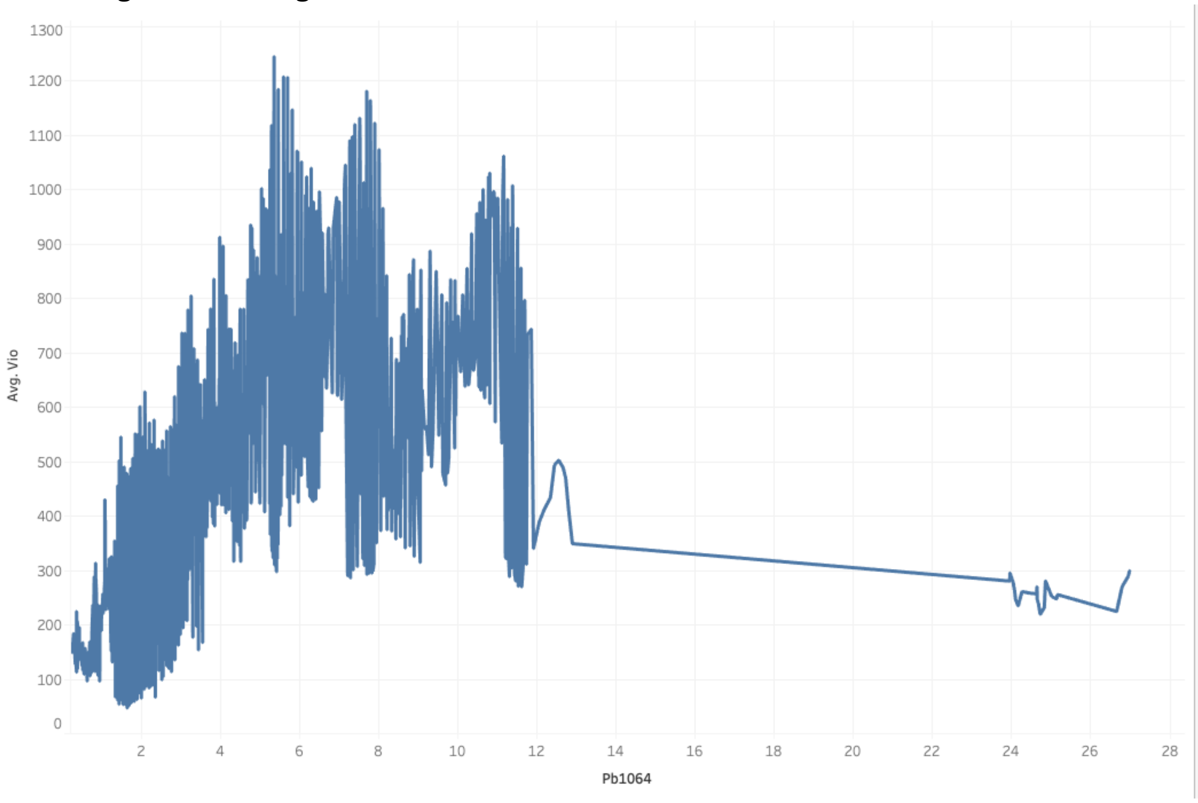


Graphs	Significance	Results Based on Our Model
Residual vs Fitted	Linearity	From the residual vs fitted graph we can see that there is a violation of an assumption. The mean residual value for every fitted value is not close to 0.
Normal Q-Q Plot	Normality	The error terms are about normally Distributed
Scale Location	Homoskedasticity	The graph suggests that there is heteroskedasticity present in the model as the red line in the graph is no where horizontal.

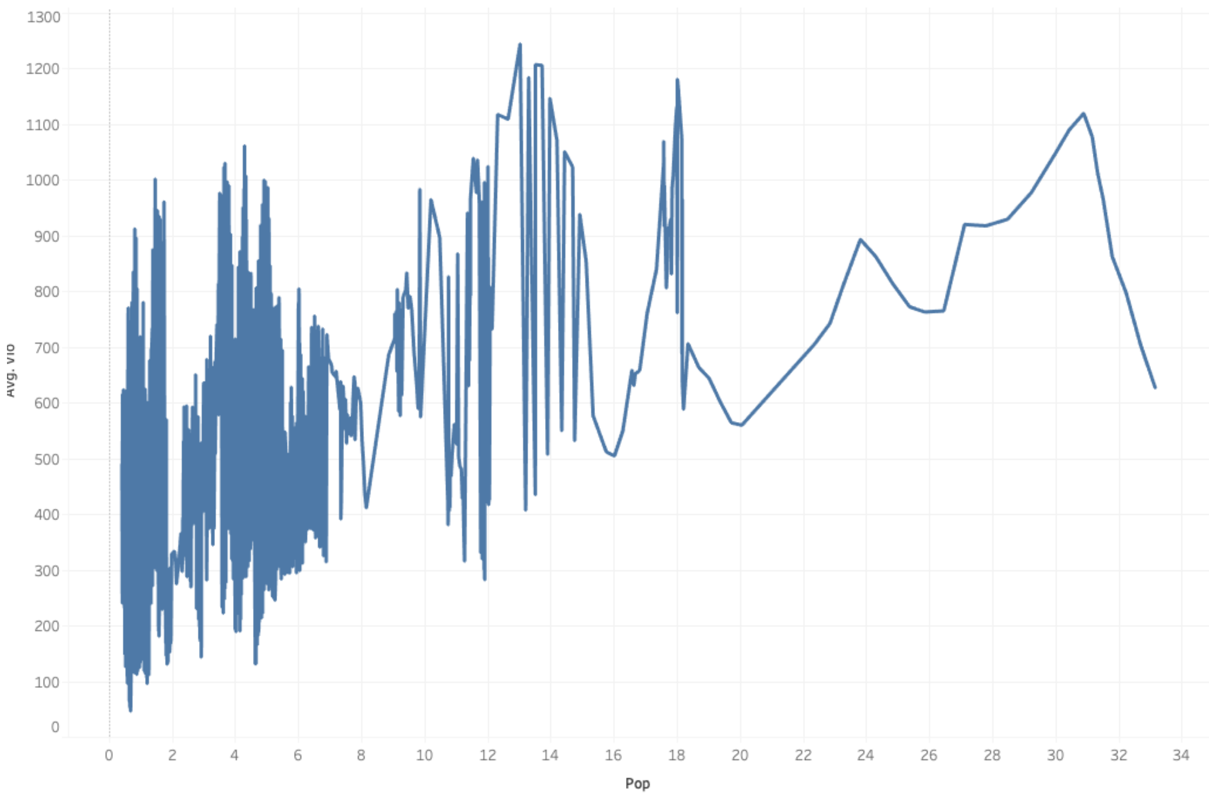
In conclusion, the assumptions of linear regression are violated , and hence OLS is not Best, Linear, Unbiased Estimator. The biasedness can be because of unobserved heterogeneity a part of which comes from interaction variables.

So we plotted graphs in tableau for every feature and the following features shows the for diminishing effect

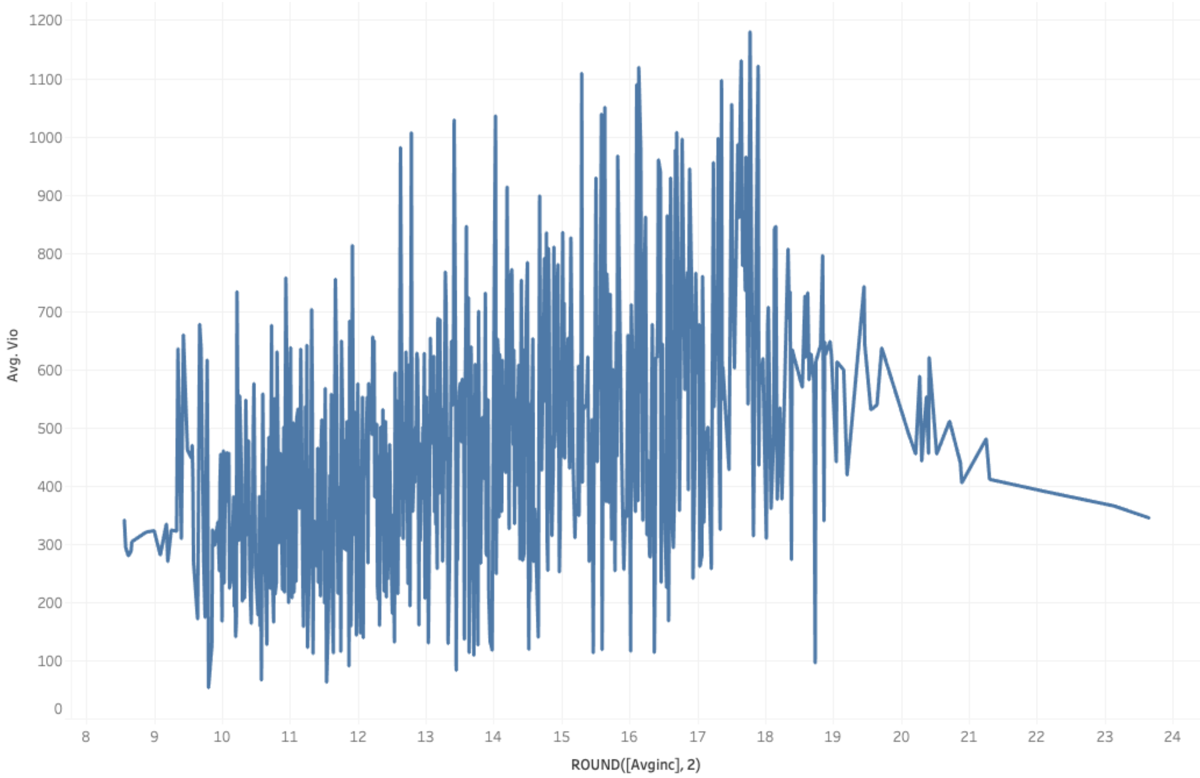
Percentage of blacks aged 10 and 64



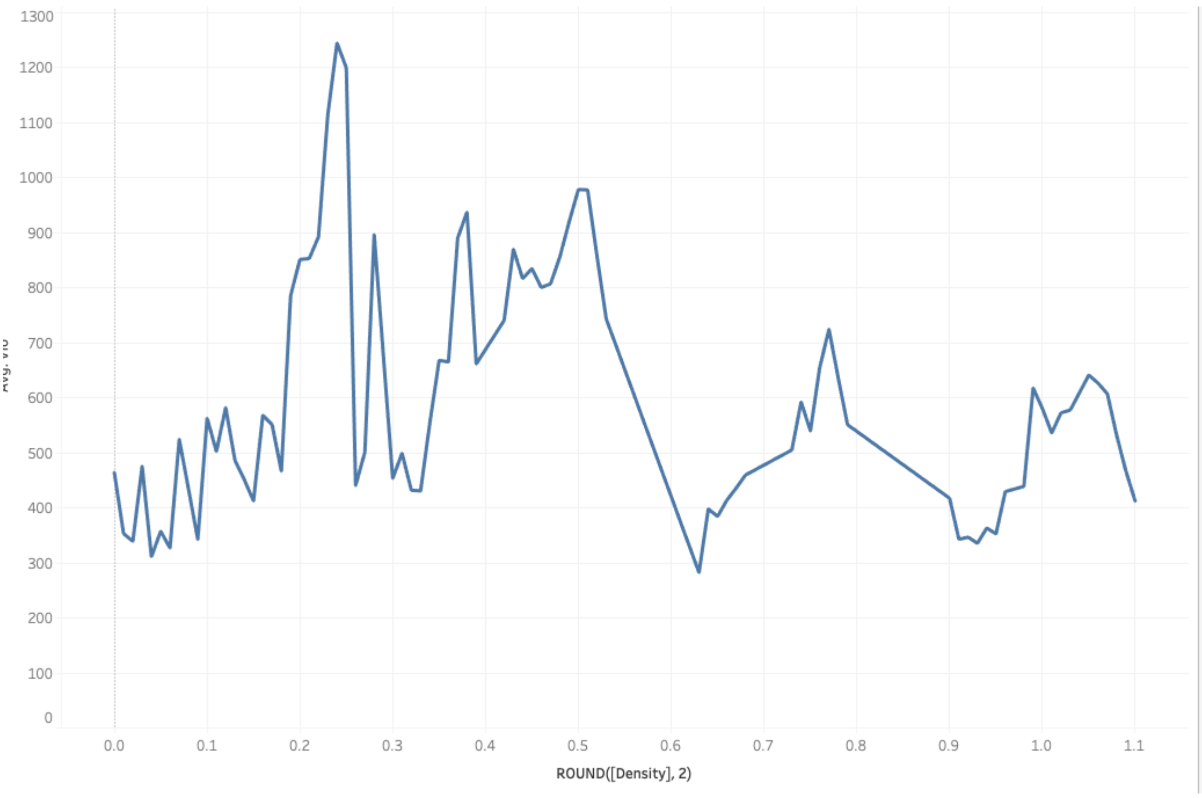
population



Average income



Population density



Based on the intuition we have included the following interaction variables

1. pw1064 white * pm1029 males
2. pw1064 white * pb1064 black
3. pm1029 male * pb1064 black
4. shall*density
5. shall*pop

Pooled OLS

A pooled model is one where the data on different individuals are simply pooled together with no provision for individual differences that might lead to different coefficients.
Until now, we have ignored the panel nature of the data , but now we will take that into consideration.
Pooling will be based on the state ids and year.

```
incarc_rate         -0.00031945  0.00010121 -3.1562           0.0016418 **
pb1064              -0.50076657  0.11589404 -4.3209 0.00001693844918677 ***
pw1064              -0.17700370  0.02669167 -6.6314 0.00000000005191121 ***
pm1029              -0.95698216  0.12351805 -7.7477 0.00000000000002110 ***
pop                 -0.02480528  0.02480497 -1.0000           0.3175234
avginc               0.16041458  0.02693806  5.9549 0.00000000349143601 ***
density              0.97478575  0.60690796  1.6062           0.1085265
shall               -0.14757518  0.02423505 -6.0893 0.00000000156239976 ***
I(pb1064^2)          0.00683417  0.00243767  2.8036           0.0051426 **
I(pw1064 * pm1029)   0.01258335  0.00164077  7.6692 0.00000000000003782 ***
I(pw1064 * pb1064)   0.00477097  0.00128039  3.7262           0.0002042 ***
I(pm1029 * pb1064)   0.01968363  0.00322111  6.1108 0.00000000137189724 ***
I(pop^2)             0.00036238  0.00048512  0.7470           0.4552291
I(avginc^2)         -0.00601161  0.00086614 -6.9407 0.00000000000663743 ***
I(density^2)        -0.06413942  0.03102849 -2.0671           0.0389559 *
I(shall * density)   0.66912187  0.32006194  2.0906           0.0367919 *
I(shall * pop)      -0.00040353  0.00611763 -0.0660           0.9474195
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 24.038
R-Squared:      0.34661
Adj. R-Squared: 0.30699
F-statistic: 34.4807 on 17 and 1105 DF, p-value: < 0.000000000000000222
```

R squared is 0.34661 which means that this model is only able to explain 34.65% of the variation which is far less as compared to OLS.
But on the contrary to OLS, if we use this model then **“If the shall is passed then there will be an decrease of 14.75%”**. We can say our model is performing fairly well as compared to OLS and the results are getting better and getting near to the real world’s estimate.
From the above output we can see that pop, density, I(pop^2) and I(shall * pop) are. not significant. But we will only include the insignificant interaction variables, and we are not removing the original features because there may be very less variation in the data itself.

```
Coefficients:
                       Estimate   Std. Error t-value                Pr(>|t|)
incarc_rate        -0.000381396  0.000097165 -3.9253 0.0000919747831909961 ***
pb1064             -0.550957777  0.110670195 -4.9784 0.0000007429789322466 ***
pw1064             -0.193375266  0.026448734 -7.3113 0.0000000000005054491 ***
pm1029             -1.014642853  0.123160774 -8.2384 0.0000000000000004878 ***
pop                 0.005128010  0.008271423  0.6200             0.5354068
avginc              0.152040608  0.026941289  5.6434 0.0000000211590940568 ***
density            -0.254241944  0.086996860 -2.9224             0.0035436 **
shall              -0.101742762  0.017987065 -5.6564 0.0000000196556577985 ***
I(pb1064^2)         0.007954876  0.002340573  3.3987             0.0007012 ***
I(pw1064 * pm1029)  0.013367459  0.001636184  8.1699 0.0000000000000008346 ***
I(pw1064 * pb1064)  0.004976422  0.001257254  3.9582 0.0000803330506859766 ***
I(pm1029 * pb1064)  0.020514695  0.003218049  6.3749 0.0000000002680813906 ***
I(avginc^2)        -0.005498605  0.000861054 -6.3859 0.0000000002501144775 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 24.4
R-Squared:      0.33675
Adj. R-Squared: 0.29907
F-statistic: 43.3127 on 13 and 1109 DF, p-value: < 0.0000000000000000222
```

The regression without the significant interaction variables gave the following results and we can see that if **the “shall law is passed then there will be 10% decrease in violent rates”.**

Since there is Heteroskedasticity in data the estimators obtained using pooled ols estimations are still, linear, unbiased and consistent. But it is not the best estimator.
The standard errors obtained are incorrect and confidence intervals will be wrong
.In such case we need to use Pooled OLS estimators with Cluster Robust Standard errors.

Cluster Robust Standard errors

```
t test of coefficients:

                      Estimate  Std. Error t value  Pr(>|t|)
incarc_rate        -0.00038140  0.00025509 -1.4952 0.1351552
pb1064             -0.55095778  0.24048049 -2.2911 0.0221462 *
pw1064             -0.19337527  0.06866768 -2.8161 0.0049472 **
pm1029             -1.01464285  0.30393981 -3.3383 0.0008709 ***
pop                 0.00512801  0.01268577  0.4042 0.6861192
avginc              0.15204061  0.05707139  2.6640 0.0078327 **
density            -0.25424194  0.19721776 -1.2891 0.1976171
shall              -0.10174276  0.03633968 -2.7998 0.0052026 **
I(pb1064^2)         0.00795488  0.00585507  1.3586 0.1745398
I(pw1064 * pm1029)  0.01336746  0.00412782  3.2384 0.0012377 **
I(pw1064 * pb1064)  0.00497642  0.00328783  1.5136 0.1304147
I(pm1029 * pb1064)  0.02051469  0.00827915  2.4779 0.0133648 *
I(avginc^2)        -0.00549860  0.00183415 -2.9979 0.0027791 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

In Pooled OLS model, estimators are same for all states and across all time periods. This seems to be not a good approach because there will be states where population of people living there are nice and having low crime rate and there will be states where more people in those states tends to commit crime always.

One thing according to us could have been an omitted variable is the size of family which hasn't been taken into the account. Going by the basic statistics people who have family tend to do crime less as compared to people who doesn't have a family. And thus the affect is maybe getting accumulated into the error term resulting in endogeneity. So the variables such as percent of population living in states might be correlated with error term. This unobserved heterogeneity leads to biased and inconsistent estimators. Panel Data can control this unobserved heterogeneity using Fixed effects model.

The omitted variable which is hiding in the error term results in biased estimators known as Omitted Variable bias. These omitted variables might vary over entities but not across time. In such a case we should use Entity fixed effects model.

Fixed Effects Model

```
incarc_rate         -0.00031945  0.00010121 -3.1562            0.0016418 **
pb1064              -0.50076657  0.11589404 -4.3209 0.00001693844918677 ***
pw1064              -0.17700370  0.02669167 -6.6314 0.00000000005191121 ***
pm1029              -0.95698216  0.12351805 -7.7477 0.00000000000002110 ***
pop                 -0.02480528  0.02480497 -1.0000            0.3175234
avginc               0.16041458  0.02693806  5.9549 0.00000000349143601 ***
density              0.97478575  0.60690796  1.6062            0.1085265
shall               -0.14757518  0.02423505 -6.0893 0.00000000156239976 ***
I(pb1064^2)          0.00683417  0.00243767  2.8036            0.0051426 **
I(pw1064 * pm1029)   0.01258335  0.00164077  7.6692 0.00000000000003782 ***
I(pw1064 * pb1064)   0.00477097  0.00128039  3.7262            0.0002042 ***
I(pm1029 * pb1064)   0.01968363  0.00322111  6.1108 0.00000000137189724 ***
I(pop^2)             0.00036238  0.00048512  0.7470            0.4552291
I(avginc^2)         -0.00601161  0.00086614 -6.9407 0.00000000000663743 ***
I(density^2)        -0.06413942  0.03102849 -2.0671            0.0389559 *
I(shall * density)   0.66912187  0.32006194  2.0906            0.0367919 *
I(shall * pop)      -0.00040353  0.00611763 -0.0660            0.9474195
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 24.038
R-Squared:      0.34661
Adj. R-Squared: 0.30699
F-statistic: 34.4807 on 17 and 1105 DF, p-value: < 0.000000000000000222
```

The entity in entity fixed effects Is state id.
This regression states that if "**Shall law is there then there is a 14.75% decrease in the violent crime rate"**, which again is overstated as compared pooled OLS.
From the above results we can see that the interaction variables shall*pop and pop^2 are not significant and also the original given features pop and density. Hence we would exclude the insignificant Interaction variables and re run the regression.

```
Coefficients:
                      Estimate   Std. Error t-value            Pr(>|t|)
incarc_rate        -0.000381396  0.000097165 -3.9253 0.0000919747831909961 ***
pb1064             -0.550957777  0.110670195 -4.9784 0.0000007429789322466 ***
pw1064             -0.193375266  0.026448734 -7.3113 0.0000000000005054491 ***
pm1029             -1.014642853  0.123160774 -8.2384 0.0000000000000004878 ***
pop                 0.005128010  0.008271423  0.6200             0.5354068
avginc              0.152040608  0.026941289  5.6434 0.0000000211590940568 ***
density            -0.254241944  0.086996860 -2.9224             0.0035436 **
shall              -0.101742762  0.017987065 -5.6564 0.0000000196556577985 ***
I(pb1064^2)         0.007954876  0.002340573  3.3987             0.0007012 ***
I(pw1064 * pm1029)  0.013367459  0.001636184  8.1699 0.0000000000000008346 ***
I(pw1064 * pb1064)  0.004976422  0.001257254  3.9582 0.0000803330506859766 ***
I(pm1029 * pb1064)  0.020514695  0.003218049  6.3749 0.0000000002680813906 ***
I(avginc^2)        -0.005498605  0.000861054 -6.3859 0.0000000002501144775 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 24.4
R-Squared:      0.33675
Adj. R-Squared: 0.29907
F-statistic: 43.3127 on 13 and 1109 DF, p-value: < 0.000000000000000222
```

The estimators for explanatory variables are same across all entities and across all time periods. However, the intercepts vary for each entity and if we observe now that passing shall issue laws across United States will reduce the crime rate by 10% approximately. In case of Pooled OLS we got an estimator which estimates that shall issue laws will reduce crime rate by 10% which is approximately same as that of entity fixed effects. 10% reduce in crime rate is huge and there may be chance that people will pretend as good till they get licence and start doing crime once they have guns

```
     1      2      4      5      6      8      9     10     11     12     13     15     16     17     18
19.470 19.294 19.895 19.469 19.841 19.579 19.678 19.553 23.051 20.215 19.425 17.801 19.335 19.950 19.552
    19     20     21     22     23     24     25     26     27     28     29     30     31     32     33
19.139 19.481 19.338 19.849 18.777 19.689 20.053 19.831 19.153 19.172 19.768 18.742 19.261 19.906 18.633
    34     35     36     37     38     39     40     41     42     44     45     46     47     48     49
19.718 19.969 19.988 19.337 17.907 19.489 19.544 19.756 19.356 19.639 19.745 18.685 19.606 19.723 19.523
    50     51     53     54     55     56
18.670 18.772 19.549 18.900 18.933 19.292
```

The effect of entity fixed effects across each state varies is shown above.

In case of entity fixed effects, we assumed unobservable heterogeneity is not varying over time and it is varying only across entities. However, if the unobservable heterogeneity is changing over time then the estimators are still biased only.

There may be many omitted variables which are not aware about and this might be the reason that we did not get an unbiased estimator or we did not see any improvement with entity fixed effects and pooled ols

Entity Fixed Effects

```
Coefficients:
                      Estimate  Std. Error t-value               Pr(>|t|)
incarc_rate         0.00105962  0.00012622  8.3950 < 0.00000000000000022 ***
pb1064             -0.02452659  0.15275940 -0.1606              0.8724710
pw1064             -0.17772895  0.05180227 -3.4309              0.0006232 ***
pm1029             -0.97821953  0.23629318 -4.1399          0.00003732917 ***
pop                 0.03631373  0.00629636  5.7674          0.00000001037 ***
avginc              0.37963032  0.04405359  8.6175 < 0.00000000000000022 ***
density             0.08871112  0.06112954  1.4512              0.1470013
shall              -0.38297536  0.04263262 -8.9832 < 0.00000000000000022 ***
I(pb1064^2)        -0.01180818  0.00307164 -3.8443              0.0001276 ***
I(pw1064 * pm1029)  0.01284041  0.00318245  4.0348          0.00005832542 ***
I(pw1064 * pb1064) -0.00299718  0.00162054 -1.8495              0.0646463 .
I(pm1029 * pb1064)  0.02791336  0.00625005  4.4661          0.00000876260 ***
I(pop^2)           -0.00083990  0.00023038 -3.6457              0.0002787 ***
I(avginc^2)        -0.01213907  0.00142450 -8.5216 < 0.00000000000000022 ***
I(density^2)        0.00380085  0.00597062  0.6366              0.5245192
I(shall * density) -0.72752847  0.49057806 -1.4830              0.1383519
I(shall * pop)      0.04433161  0.00971078  4.5652          0.00000553518 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    474.53
Residual Sum of Squares: 132.64
R-Squared:      0.72047
```

The output states that if the shall is passed for
With time fixed effects shall issue laws will reduce crime rate by 38% approximately. This seems to be more biased estimator than that of OLS and Pooled OLS. Ignore the insignificant Interactions

```
Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.475818 -0.224452  0.059925  0.269704  1.088801

Coefficients:
                      Estimate  Std. Error  t-value               Pr(>|t|)
incarc_rate         0.00197044  0.00012794  15.4018 < 0.00000000000000022 ***
pb1064             -0.28621359  0.11484907  -2.4921              0.012841 *
pw1064             -0.13280847  0.05811878  -2.2851              0.022489 *
pm1029             -0.73845982  0.26362826  -2.8011              0.005179 **
pop                 0.08124367  0.00642777  12.6395 < 0.00000000000000022 ***
avginc              0.22662945  0.04714562   4.8070            0.000001737 ***
density             0.02279481  0.01377263   1.6551              0.098184 .
shall              -0.45490788  0.04385324 -10.3734 < 0.00000000000000022 ***
I(pw1064 * pm1029)  0.00996424  0.00355779   2.8007              0.005186 **
I(pm1029 * pb1064)  0.02195018  0.00694379   3.1611              0.001613 **
I(pop^2)           -0.00207114  0.00024545  -8.4382 < 0.00000000000000022 ***
I(avginc^2)        -0.00735337  0.00151811  -4.8438            0.000001450 ***
I(shall * pop)      0.03350815  0.00752054   4.4556            0.000009194 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    474.53
Residual Sum of Squares: 169.6
R-Squared:      0.64259
```

Even after ignoring the insignificant interaction the decrease in crime rates is 45% which is huge and it is practically not imaginable as well.

The estimator of shall issue laws seems to be biased because it is overstating that passing shall issue laws reduce crime rate by 45 %. This might be a problem because may be the government passed laws across some states which are more prone to crimes. In such a case as we are ignoring this nature it might be correlated with explanatory variable, and the exact interpretation of reduce in crime rate estimation , how much it is coming from error term and how much is coming from explanatory variable cannot be separated. As a result, the estimator will be biased. In such a case use fixed effects model varying across each state and also over time

term	estimate	std.error	statistic	p.value
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
incarc_rate	−0.0002236755	0.00009926453	−2.2533270	0.024437944993182817
pb1064	−0.3970482057	0.11228494084	−3.5360771	0.000423289612338476
pw1064	−0.0681195717	0.02621788839	−2.5982097	0.009498355189972206
pm1029	−0.1954382716	0.12957139514	−1.5083443	0.131758091233939029
pop	−0.0244318615	0.02251389995	−1.0851901	0.278078964448561949
avginc	0.1225902505	0.03100693815	3.9536393	0.000081966773736370
density	−0.3363866565	0.55219330184	−0.6091828	0.542531052374750078
shall	−0.1283532543	0.02268415957	−5.6582768	0.000000019563000098
I(pb1064^2)	0.0102588630	0.00245631999	4.1765173	0.000031980294909102
I(pw1064 * pm1029)	0.0038512952	0.00163475854	2.3558801	0.018656351482304292
I(pw1064 * pb1064)	0.0056718942	0.00122553167	4.6281091	0.000004136443500133
I(pm1029 * pb1064)	0.0020390922	0.00328815144	0.6201333	0.535300487017933757
I(pop^2)	0.0002350789	0.00043969175	0.5346449	0.593005188134278383
I(avginc^2)	−0.0041101054	0.00095310205	−4.3123455	0.000017626380981990
I(density^2)	0.0052585804	0.02824265275	0.1861929	0.852328388340030552
I(shall * density)	0.7336665646	0.28717404755	2.5547802	0.010761328409380417
I(shall * pop)	0.0015442406	0.00552606491	0.2794467	0.779955394924284562
factor(year)78	0.0424540947	0.02690118741	1.5781495	0.114823298326261258
factor(year)79	0.1458795471	0.02763274697	5.2792271	0.000000156689710843
factor(year)80	0.2051993326	0.02835177846	7.2376177	0.000000000000863516
factor(year)81	0.1969529346	0.03017034239	6.5280311	0.000000000102201024
factor(year)82	0.1795611326	0.03241180416	5.5399919	0.000000037964826753
factor(year)83	0.1426785336	0.03585487265	3.9793346	0.000073707770697989
factor(year)84	0.1667321962	0.04149388796	4.0182351	0.000062688545371933
factor(year)85	0.2158634190	0.04663283213	4.6290008	0.000004119017299455
factor(year)86	0.2971902843	0.05238865746	5.6727982	0.000000018018271205
factor(year)87	0.2982220706	0.05800578081	5.1412474	0.000000323683115744
factor(year)88	0.3589897588	0.06379840676	5.6269392	0.000000023347903911
factor(year)89	0.4128748293	0.06967616088	5.9256254	0.000000004175978159
factor(year)90	0.4971942522	0.08044702114	6.1803936	0.000000000903963789
factor(year)91	0.5544673231	0.08497761237	6.5248635	0.000000000104300817
factor(year)92	0.5875502280	0.09006923179	6.5233179	0.000000000105340702
factor(year)93	0.6093934227	0.09410757140	6.4754983	0.000000000143036443
factor(year)94	0.5953075478	0.09877381044	6.0269776	0.000000002287354462
factor(year)95	0.5953910524	0.10305135204	5.7776151	0.000000009895926095
factor(year)96	0.5415002440	0.10673219218	5.0734482	0.000000459433838506
factor(year)97	0.5227028370	0.10970063227	4.7648115	0.000002147466610136
factor(year)98	0.4710259628	0.11304056164	4.1668756	0.000033340405120953
factor(year)99	0.4157225320	0.11611829351	3.5801640	0.000358599236005665

According to entity and time fixed effects the decrease in crime rate is 12.83% which is worse than the pooled OLS. Let us remove insignificant variables and see.

term	estimate	std.error	statistic	p.value
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
incarc_rate	-0.000226237	0.00009535284	-2.3726304	0.017835171904381306
pb1064	-0.487358662	0.10785077438	-4.5188239	0.000006898951500809
pw1064	-0.092795272	0.02566007159	-3.6163294	0.000312520567090053
pm1029	-0.295978272	0.12797685405	-2.3127485	0.020922506628733049
pop	-0.005285439	0.00756535044	-0.6986376	0.484927953831768455
avginc	0.136262984	0.03091512734	4.4076475	0.000011485382522234
density	-0.215532757	0.07936570866	-2.7156912	0.006718617223387557
shall	-0.067086030	0.01674085571	-4.0073238	0.000065594783729912
I(pb1064^2)	0.011274059	0.00238656561	4.7239676	0.000002615549272721
I(pw1064 * pm1029)	0.005080114	0.00161688313	3.1419180	0.001723826173053905

After removing the insignificant interaction we are getting the decrease in crime to be 6.7% and the estimator is linear, unbiased and consistent. However, the standard errors are still incorrect and we can calculate the standard errors by cluster robust standard errors.

Comparison

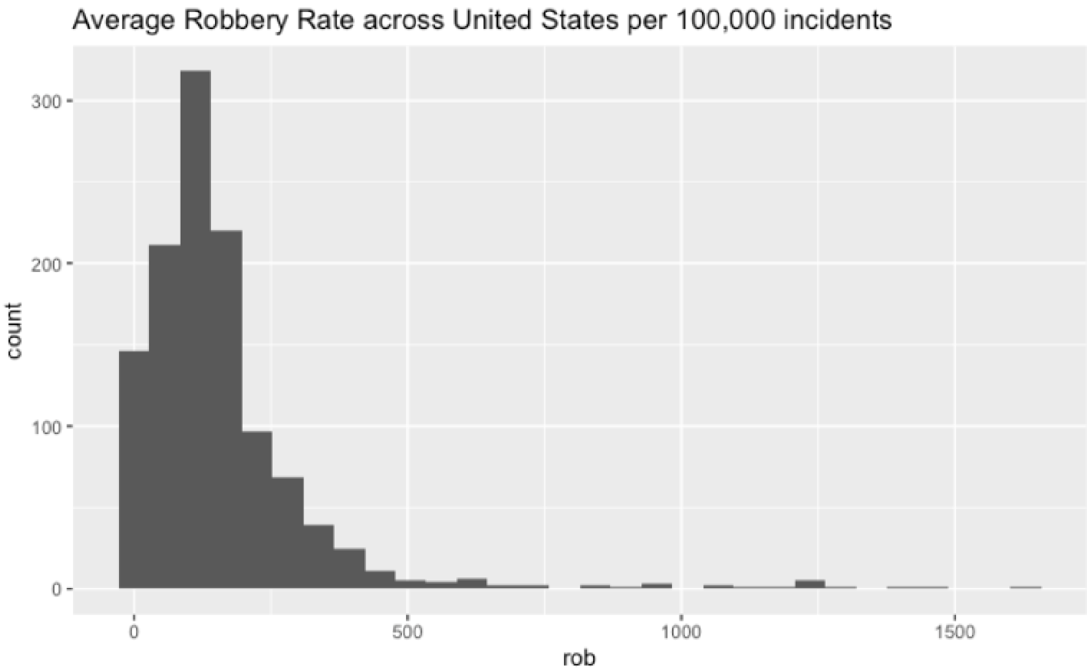
Panel results with td, adding fixed effects

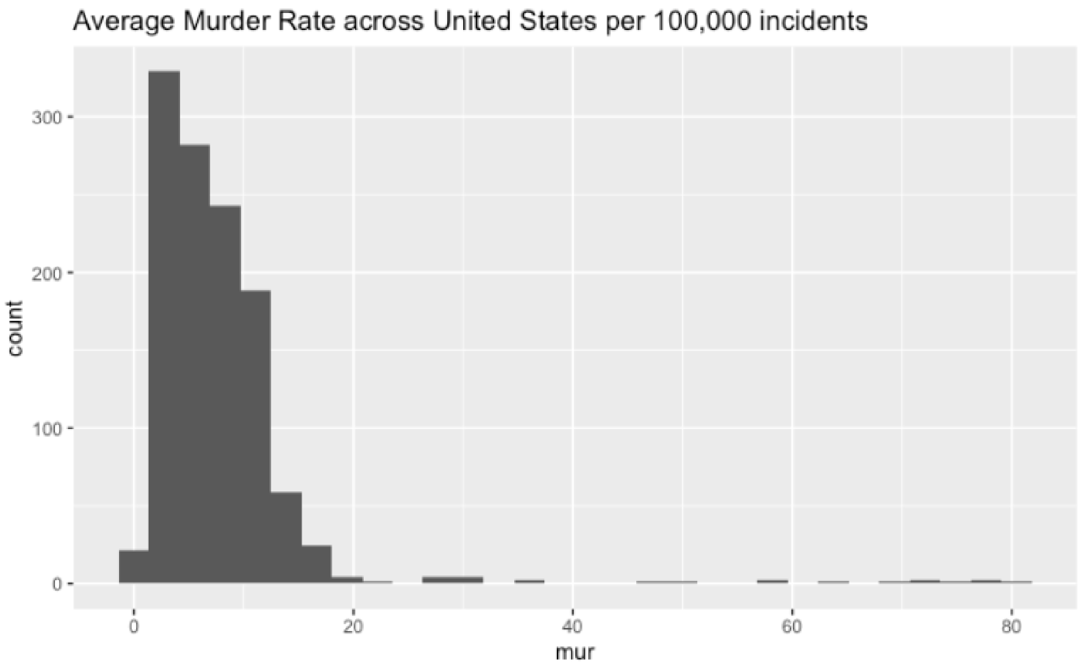
	Dependent variable:			
	vio			
	panel with robust SE (1)	entity fixed effects (2)	time fixed effects (3)	entity and time fixed effects (4)
incarc_rate	-0.0004 (0.0003)	-0.0004 (0.0003)	0.002*** (0.0002)	-0.0002 (0.0002)
pb1064	-0.551** (0.240)	-0.551** (0.240)	-0.286*** (0.103)	-0.487* (0.266)
pw1064	-0.193*** (0.069)	-0.193*** (0.069)	-0.133*** (0.051)	-0.093 (0.069)
pm1029	-1.015*** (0.304)	-1.015*** (0.304)	-0.738*** (0.210)	-0.296 (0.320)
pop	0.005 (0.013)	0.005 (0.013)	0.081*** (0.003)	-0.005 (0.014)
avginc	0.152*** (0.057)	0.152*** (0.057)	0.227*** (0.033)	0.136 (0.084)
density	-0.254 (0.197)	-0.254 (0.197)	0.023* (0.012)	-0.216* (0.130)
shall	-0.102*** (0.036)	-0.102*** (0.036)	-0.455*** (0.051)	-0.067* (0.039)
I(pb10642)	0.008 (0.006)	0.008 (0.006)		0.011* (0.007)
I(pw1064 * pm1029)	0.013*** (0.004)	0.013*** (0.004)	0.010*** (0.003)	0.005 (0.004)
I(pw1064 * pb1064)	0.005 (0.003)	0.005 (0.003)		0.006* (0.004)
I(pm1029 * pb1064)	0.021** (0.008)	0.021** (0.008)	0.022*** (0.006)	0.004 (0.009)
I(pop2)			-0.002*** (0.0001)	
I(avginc2)	-0.005*** (0.002)	-0.005*** (0.002)	-0.007*** (0.001)	-0.004* (0.002)

We cannot use Random Effects for this model because these entities are not coming from Random Population. All these entities are states in the country United states and they are not random in nature. Based on the above analysis we observe that violent crime will reduce and shall issue laws are playing some significant impact. 6% reduction in crime rate by passing shall issue laws is acceptable and it seems to be realistic rather than overstating

Murder Rate & Robbery Rate

As of now we analysed only if shall issue laws were affecting the crime rate. However, the robbery and murder rates are also considered as crimes and we further analyse that if the shall issue laws are playing any significant role in affecting these two.
Also, we observed that there is a high correlation between crimes, murder and robbery rate.





Considering the effect of shall law on violent crimes the best estimator was entity and time fixed effects, now we will use the same for the estimation of the effects of shall law on murder rate and robbery rate.

Robbery Rate:

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>
incarc_rate	3.136993e-05	0.0001247797	0.251402400
pb1064	1.410778e-02	0.0313621793	0.449834138
pw1064	-1.283223e-02	0.0108654945	-1.181007156
pm1029	1.046049e-01	0.0215796584	4.847385060
pop	1.638844e-05	0.0108735238	0.001507187
avginc	1.435688e-02	0.0088935852	1.614295836
density	-4.474487e-02	0.1054279041	-0.424412055
shall	2.682977e-02	0.0237134722	1.131414833
factor(year)78	3.284970e-02	0.0388879394	0.844727269
factor(year)79	1.375917e-01	0.0395200825	3.481562990

Murder Rate:

term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>
incarc_rate	-0.0001164045	0.0001307712	-0.89013851
pb1064	0.0219832693	0.0328680833	0.66883332
pw1064	-0.0004893302	0.0113872182	-0.04297188
pm1029	0.0691941129	0.0226158394	3.05954211
pop	-0.0320769250	0.0113956330	-2.81484364
avginc	0.0566491650	0.0093206246	6.07782930
density	-0.5442635260	0.1104901895	-4.92589911
shall	-0.0149523734	0.0248521116	-0.60165404
factor(year)78	-0.0007194958	0.0407552045	-0.01765408
factor(year)79	0.0592481186	0.0414177010	1.43050235

Both the regressions indicate that the coefficient of shall isn't significant. Hence, we cannot make any valuable conclusions.

Conclusion

- We see that from the regression models, the shall-issue laws have significantly decreased violent crime rate by 6%. Even though we see a drop in robbery rates by 2.68% it is not significant and hence no conclusion can be drawn about it. The same is the case with murder rate.
- We conclude that violent crime rates reduce but we need more variables to arrive at a strong conclusion regarding the effect of shall-issue laws on crime.

Limitations

The analysis doesn't resolve the debate of whether all crimes will reduce in US if shall-issue laws are implemented. We need more data related to characteristics of states, like unemployment rate, area of state. Further analysis can also be done on other crimes in US like burglary and vehicle theft.

Also, analysis on whether decrease in crime rate in one category is leading to increase in crime rate in another.