Do more Guns Reduce Crime in US?

BUAN 6312

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Do more Guns reduce Crime?

OVERVIEW

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 defenseless. 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 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 for the applicant to demonstrate "good cause".

We have analyzed the historical data on crime in the U.S to answer the question "Do shall-issues law reduce crime-or not.

GUNS DATASET SAMPLE

	year	vio	mur	rob	incarc_rate	pb1064	pw1064	pm1029	pop	avginc	density
24	77	443	10.8	96.8	63	7.836	62.1	22.4	0.403	20.30	0.00070
25	78	442	12.9	91.3	75	7.946	62.7	22.1	0.405	19.04	0.00071
26	79	491	13.3	109.6	127	8.057	63.1	22.0	0.403	18.12	0.00070
27	80	436	8.9	81.8	133	8.124	62.7	21.6	0.405	17.90	0.00071
28	81	616	14.6	114.6	143	8.154	62.8	21.0	0.418	18.08	0.00073
29	82	624	18.5	133.8	170	8.149	62.9	20.3	0.450	18.97	0.00078
30	83	614	13.8	97.1	194	8.114	62.9	19.5	0.488	19.05	0.00085
31	84	622	11.6	109.4	219	8.095	62.4	18.9	0.514	18.59	0.00090
32	85	582	9.8	92.9	252	8.054	61.9	18.2	0.532	18.71	0.00093
33	86	570	8.6	88.0	288	8.082	61.3	17.8	0.544	17.91	0.00095
34	87	455	10.1	73.1	306	8.185	60.4	17.5	0.539	16.96	0.00094
35	88	523	5.7	72.9	339	8.392	60.1	17.2	0.542	16.74	0.00094
36	89	498	8.0	67.6	355	8.556	59.8	17.1	0.547	17.29	0.00095
37	90	524	7.5	76.7	361	8.631	60.1	17.0	0.553	17.31	0.00097
38	91	614	7.4	113.2	348	8.527	60.4	16.6	0.569	17.01	0.00099
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Showing 1 to 16 of 575 entries, 14 total columns

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 is a total of 51 states × 23 years = 1173 observations.

Variable Description

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
Stated	ID number of states (Alabama = 1, Alaska = 2, etc.)
Year	Year (1977-1999)

Dependent variables: (VIO; ROB; MUR): Combined to form totalCrime
Regressors: INCARC_RATE, DENSITY, AVGINC, POP
Indicator Variables: SHALL, PM1029, PW1064, PB1064
Entity: STATEID
Time Period: YEAR

Effect of Variables on Violent Crime Rate (Our expectations according to 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 the 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 either increase or decrease the crime rate.
- AVGINC: The real per capita personal income in the state should reduce the crime rate, therefore an inverse relation.
- POP: More the state population, the 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 increases the chances of crime. Therefore, it will have a positive relationship with the crime rate.
- PW1064 and PB1064: The effect of these two variables, according to economic theory, are highly contrasting. The effect of the population of blacks increases the crime rate as compared to the 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.

EXPLORATORY DATA ANALYSIS

It makes sense for us to analyze the data visually before attempting an answer on the impact of guns on crime. We start our analysis by plotting the average crime and the number of states with shall-issue laws. As seen from the plot (Exhibit 1), the average crime rises from 1984 to 1994 only to recede towards the fag end of the time period. What is also evident is an increase in the number of states with the shall-issue law with as many as 28 states implementing the law.

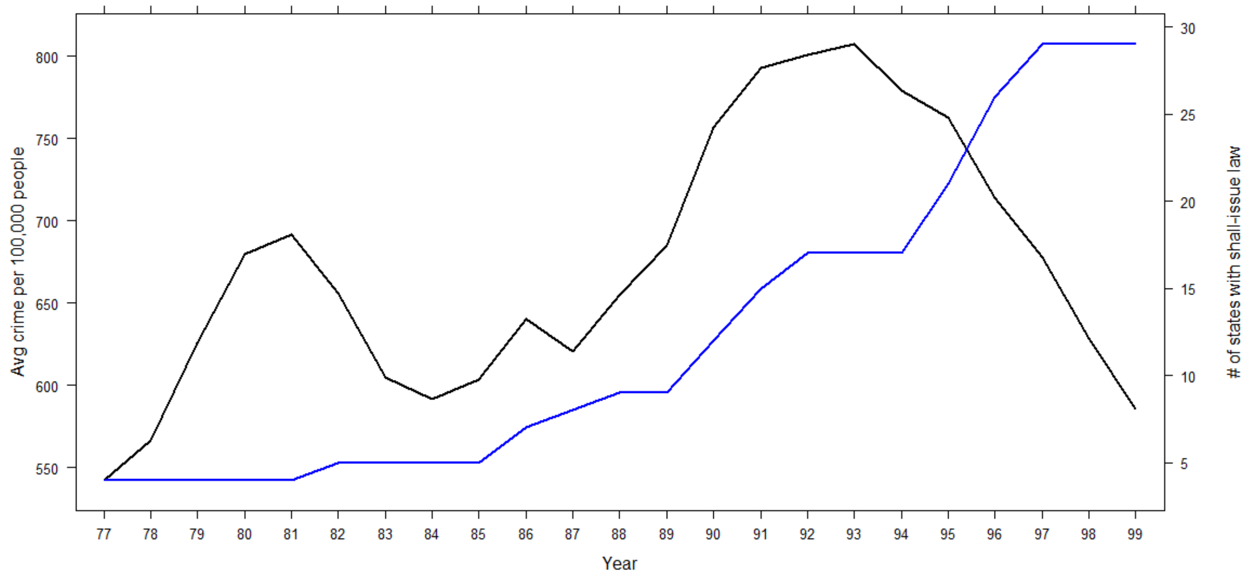


Exhibit 1

Exhibit 2 shows the implementation status of the law over the years. It is interesting to note that as many as 26 states either had the law, to begin with, or never implemented one. For our analysis, we will filter out these states since the variation of crime in these states is not a function of shall-issue laws.

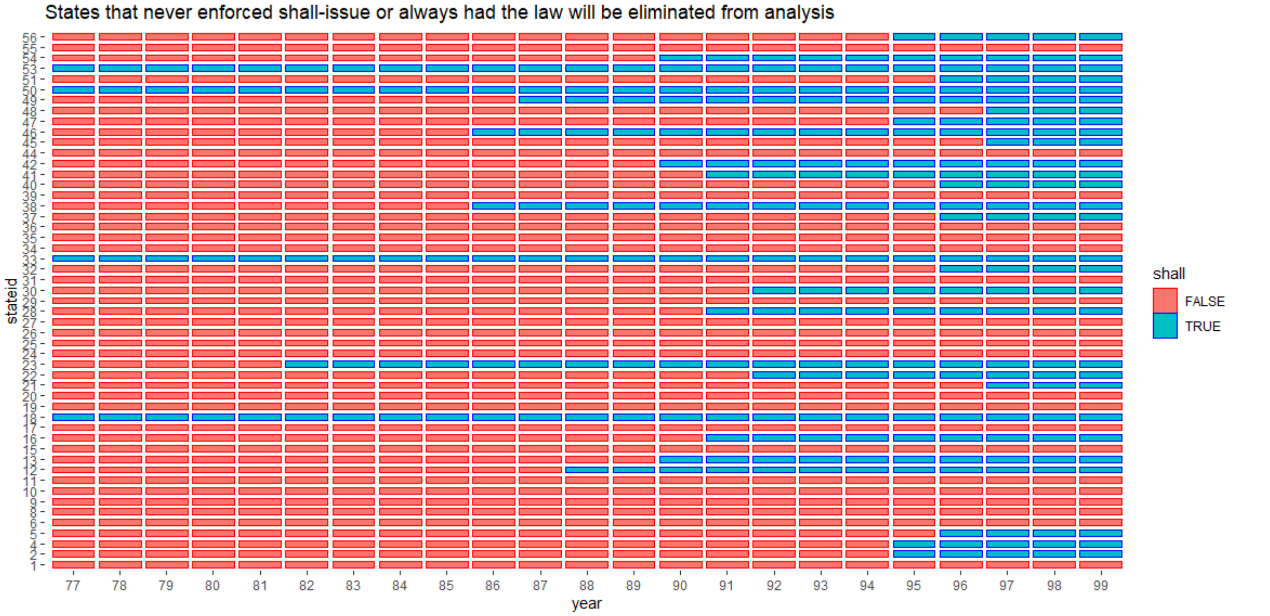


Exhibit 2

Exhibit 3 is a plot of states that shows the implementation status of shall-issue laws for the remaining 25 states that would be taken into analysis hereon.

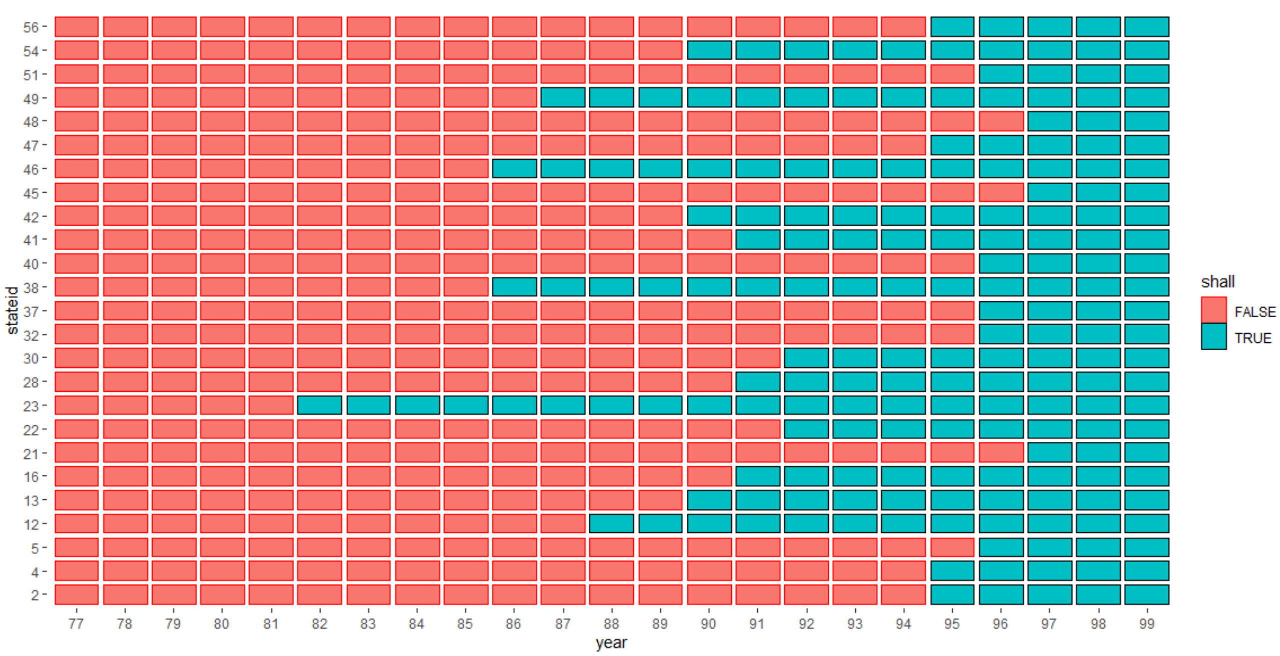


Exhibit 3

Exhibit 4 is a heatmap of crime over the years and states. Stateid 12 stands out by the sheer number of total crimes over the years.

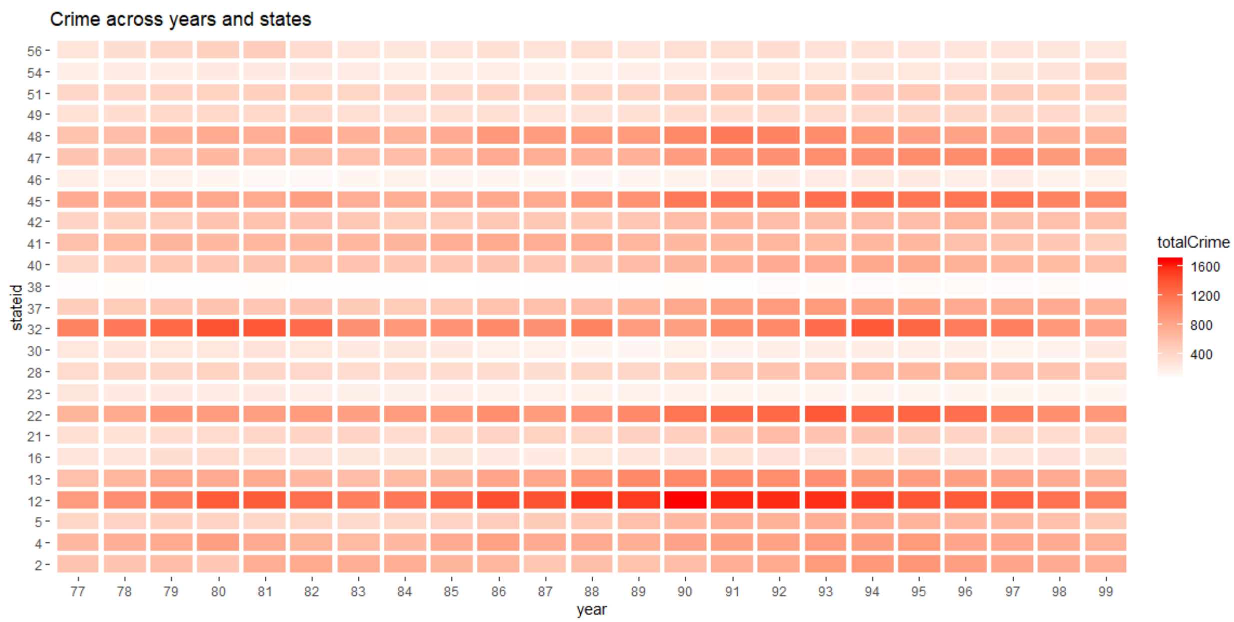


Exhibit 4

Average crime rate variation for the states (Exhibit 5) after filtering out the states above still shows a similar pattern as in Exhibit 1.

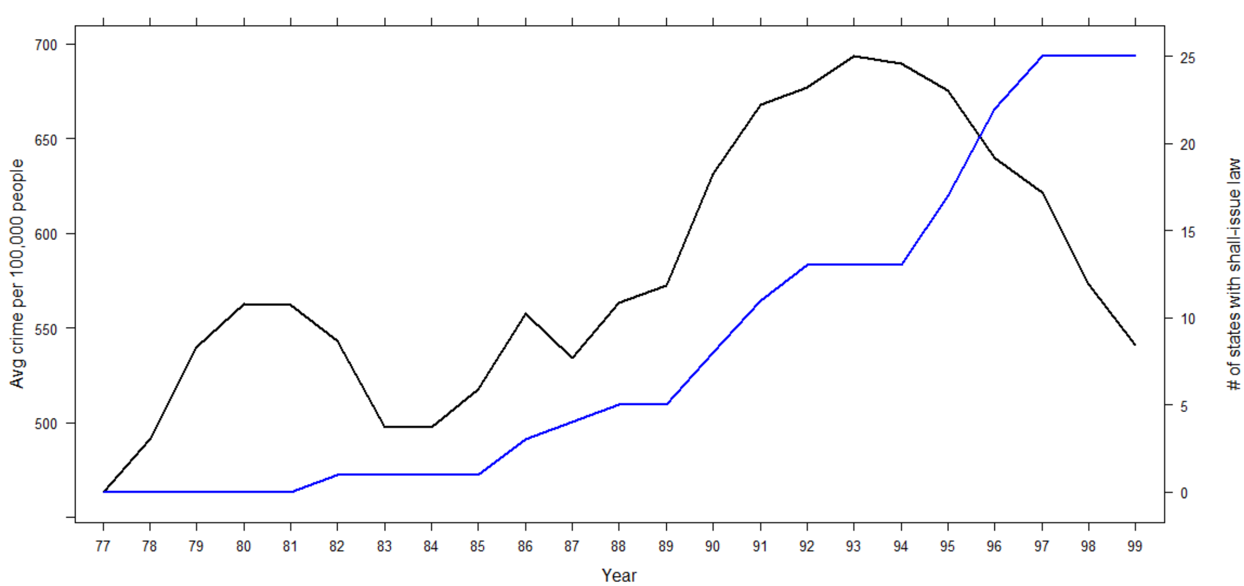


Exhibit 5

It is rather interesting to note that states with higher black population witness higher average crime rates. The contrary is true for the white population as evident from Exhibit 6. A word of caution - correlation does not mean causation.

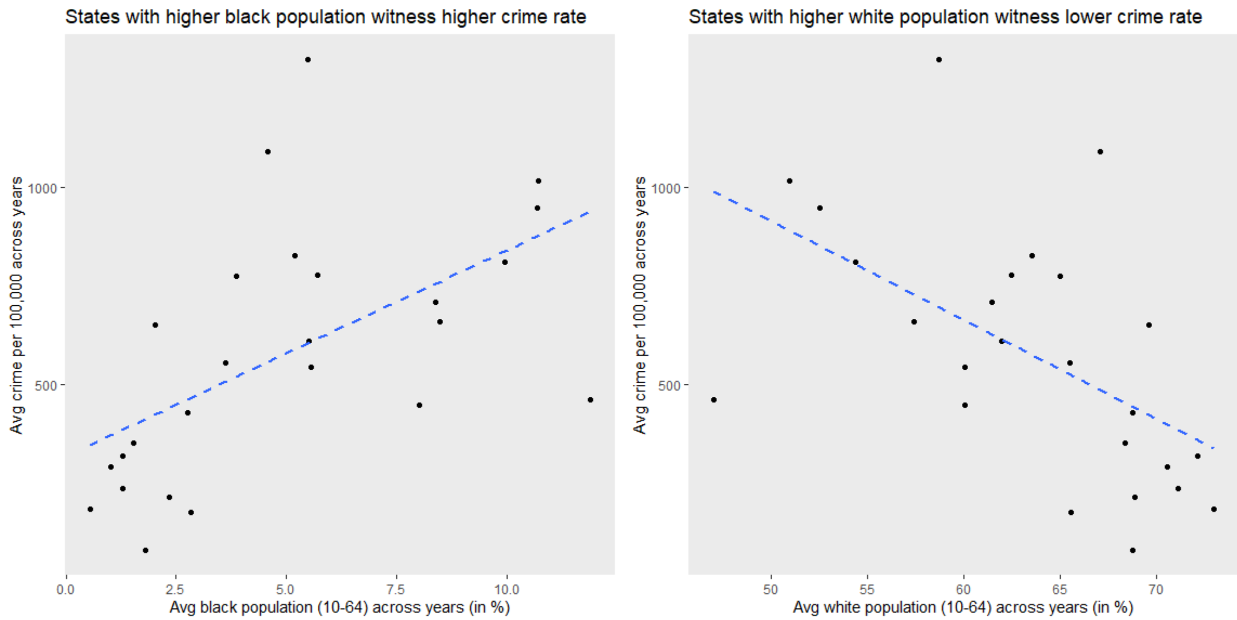
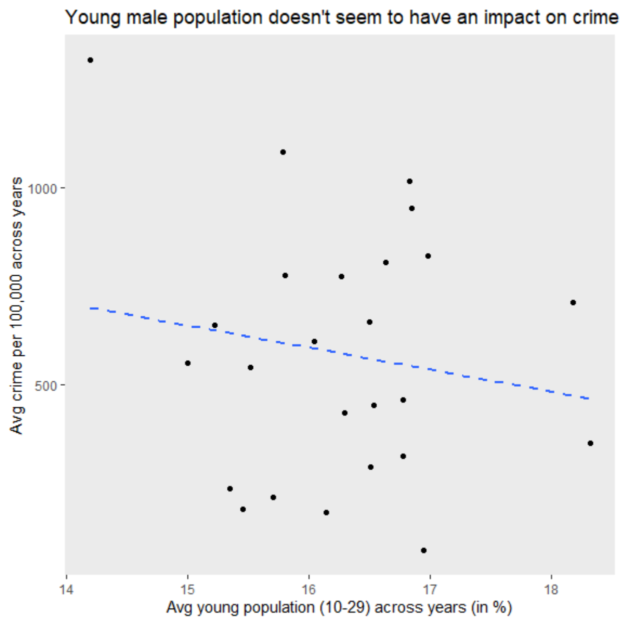


Exhibit 6

The young male population aged 10-29 seems to have very little impact on the average crime. On the other hand, an increase in the average income increases the average crime. Perhaps, it's the income disparity!



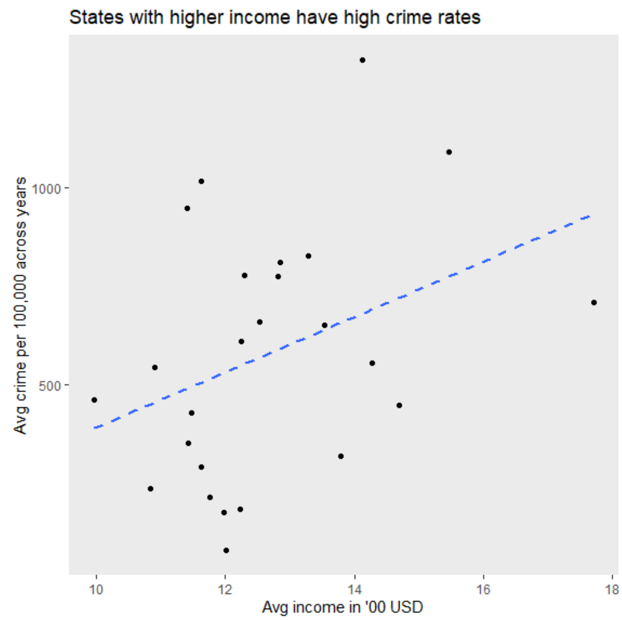


Exhibit 7

Exhibit 8 suggests that states with higher population density tend to have higher crime rates.

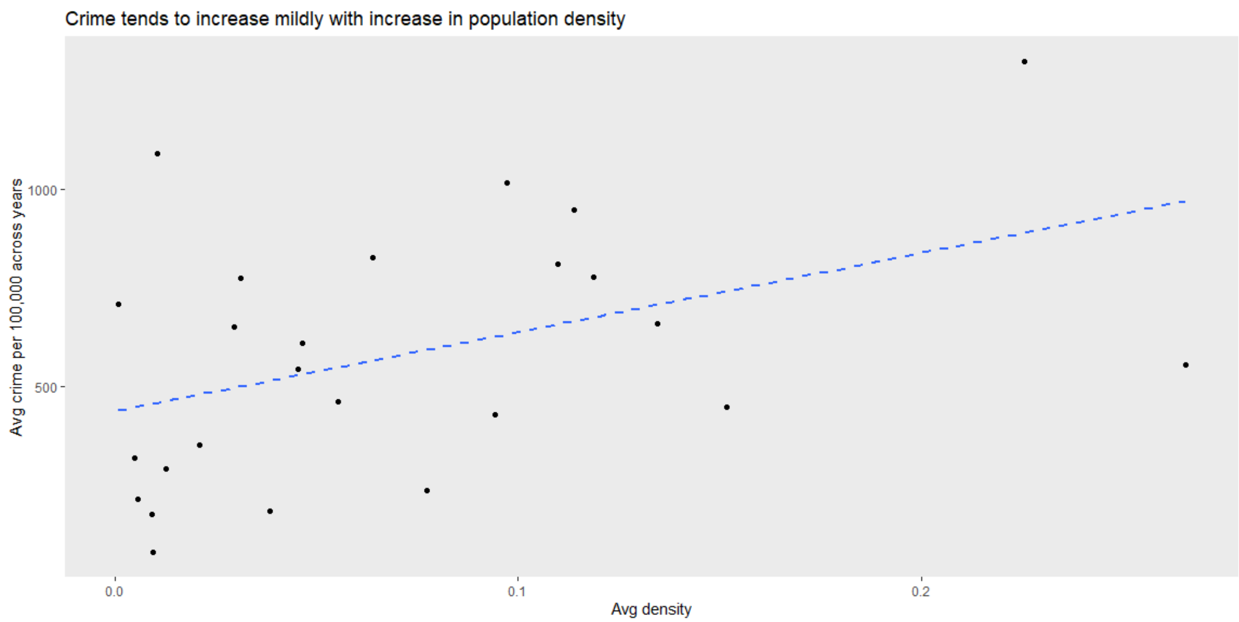
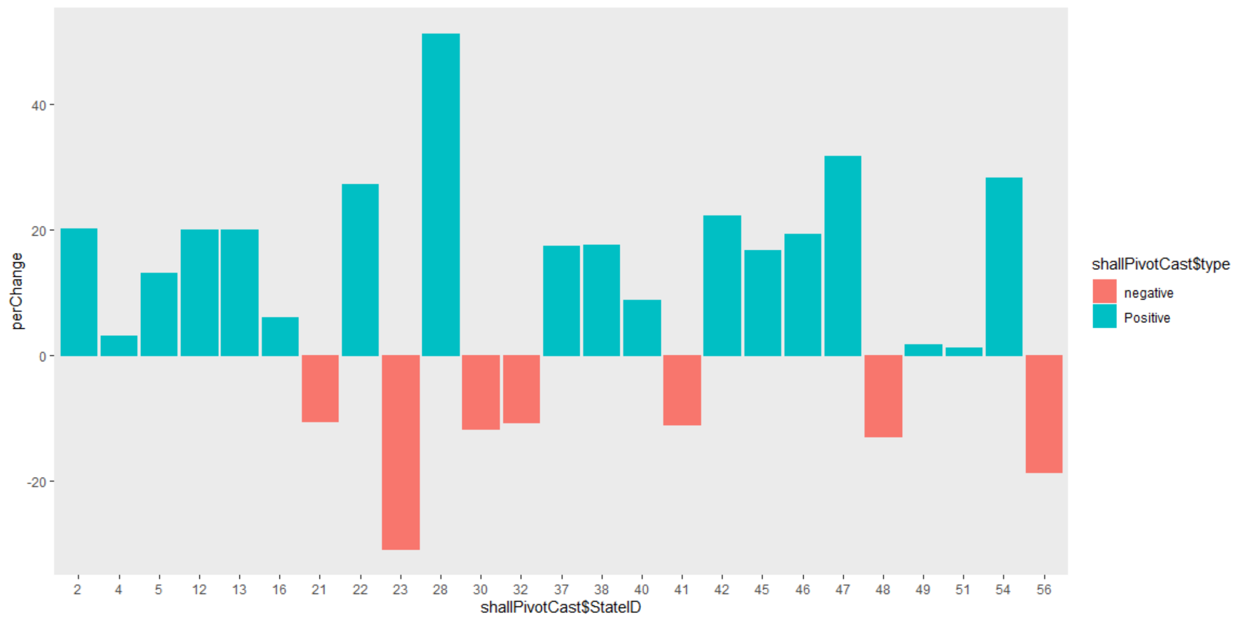


Exhibit 8

Exhibit 9 shows average crime for states without is consistently higher for states with shall-issue laws. Is it because of the law or maybe the states that implemented the shall-issue laws always had low crimes, to begin with. The exhibit below could very well be misleading.

Exhibit 9

And misleading it is? Only 7 of the 25 states witnessed a percentage decrease in average crime after implementing the shall-issue law. This is evident from the plot that shows the percentage change in crime after the law implementation across the states summarized over the years (Exhibit 10).



40
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shallPivotCast$StateID
shallPivotCast$type
negative
Positive

Exhibit 10

Modeling

Through modeling the data we are trying to understand three main relationships

1.The effect of the shall Carry law on the total rate in the US
2.Understand how the incarceration rate affects total crime rate in the US
3.Understand which of variables have a significant impact on total crime

To help us carry out the above goals we run 4 models to estimate the relationship between the shall carry law, incarceration rate together with other control variables as explanatory variables with the dependent variable total crime rate. Following four models have been run to estimate the relationship between the dependent and the explanatory variables:

- The Pooled OLS Model
- Least squares dummy variable model
- The Entity Fixed Effects Model
- The Time and Entity Fixed Model

To get a better model fit we have also done some log transformations in the model

    - totalCrime rate -----> ln(totalCrime)
    - density --------------> ln(density)
    - incarceration rate -------------> ln(incarc_rate)

In all the models we will have the following variables

- Dependent variable: log (totalCrime)
- Independent variables:
    - log(incarc_rate)
    - pb1064
    - pm1029
    - pop
    - avginc
    - log(density)
    - shall (categorical variable), where
    - shall=1 (states which have implemented shall law)
    - shall=0 (states which haven't implemented shall law)
    - pw1064

Model 1 : Pooled Ordinary Least Squares Model

The dataset that we are dealing with is a panel data having 25 entities(states) that have been followed for 23 years. The least squares estimator, when applied to a panel data model, is referred to as pooled least squares .
We start with this model because this is the most rudimentary model in case of modelling panel data where the central idea is that the data for different individuals are pooled together, and the equation is estimated using least squares, in this particular case there is no provision for individual differences that might lead to different coefficients for each state or year.

The regression output is given below:

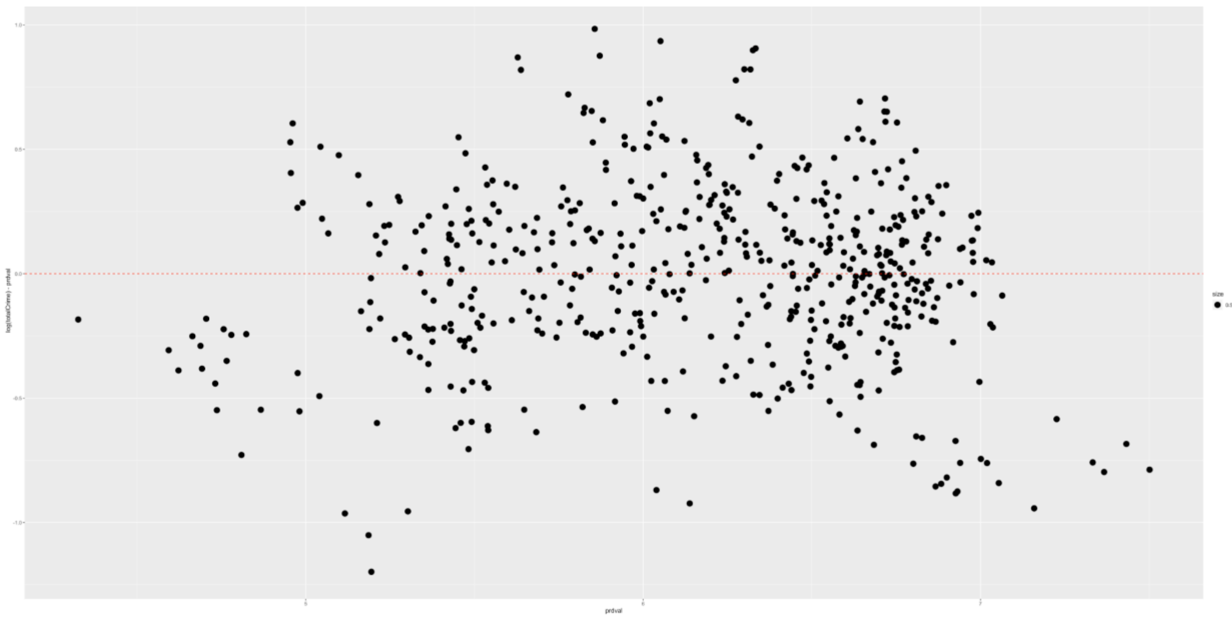
```
Pooling Model

Call:
plm(formula = log(totalCrime) ~ shall + log(incarc_rate) + pb1064 +
    pw1064 + pm1029 + pop + avginc + log(density), data = guns_panel,
    model = "pooling")

Balanced Panel: n = 25, T = 23, N = 575

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
-1.1981 -0.2168  0.0168  0.2322  0.9841

Coefficients:
                 Estimate Std. Error t-value Pr(>|t|)
(Intercept)       1.81343    0.62780    2.89  0.00402 **
shallTRUE        -0.35700    0.03944   -9.05  < 2e-16 ***
log(incarc_rate)  0.78126    0.04314   18.11  < 2e-16 ***
pb1064           -0.06951    0.02128   -3.27  0.00116 **
pw1064           -0.03209    0.00964   -3.33  0.00092 ***
pm1029            0.12017    0.01515    7.93  1.2e-14 ***
pop               0.00750    0.00593    1.26  0.20665
avginc            0.10340    0.01255    8.24  1.2e-15 ***
log(density)      0.17195    0.01981    8.68  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    273
Residual Sum of Squares: 73.6
R-Squared:      0.73
Adj. R-Squared: 0.726
F-statistic: 191.207 on 8 and 566 DF, p-value: <2e-16
```

Interpretation

From the table above we can see that the states which implemented the shall law have 35.7% less total crime rate than the states which haven’t implemented the shall law-keeping all the other variables constant.
We think this estimate is not accurate as reduction is a crime by 35% where shall law seems to be in effect certainly too large to be real. Hence we feel that the estimate

is certainly downwardly biased. The real effect may be much smaller than this.

Also, we suspected the presence of heteroskedasticity. So we plotted a residual plot against the fitted values of our dependent variable and look for any kind of pattern, if we find any kind of pattern we say that the informal test shows the presence of heteroskedasticity



We can see an inverted U shaped pattern formed by the residuals indicating there is something systematic about the variance of errors that we are not capturing in our model and therefore pointing towards presence of heteroskedasticity.
We should look for other models to fit the data because pooled OLS models are ineffective in the case of heteroskedasticity in the data. Fixed effects model

Model 2 : Fixed Effects within Entity (state) Model

FE estimator allows us to control for unobserved heterogeneity, and obtain unbiased and consistent estimators to variables that are endogenous with OLS. The entity fixed model accounts for deviations from the mean, the coefficient estimates depend only on the variation of the dependent and explanatory variable within individuals.

We decided to use the Entity Fixed Model which accounts for unobserved heterogeneity that is time-invariant or is constant over time but varies between states. Our assumption in doing so is the individual characteristics of one state are not correlated with other states and the difference between states is fixed. We think this assumption will be reasonable because the US states are culturally very diverse and we think each is different from others in a constant fashion.

The fixed-effects model is less efficient than the pooled and random-effects model because we only take advantage of variation within entities(states) and not the variation between entities(states) hence we are limiting the amount of information we are making use of to estimate the model and hence our entity fixed model is less efficient.

One disadvantage of the fixed effects model is that the time-invariant variables cannot be estimated by the model and are not anymore in the model or the variables that are not varying significantly in the model would not be properly estimated because we are not having significant changes in the x side to interpret the variation in the dependent variable y.

The regression output for the entity fixed model is given below:

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(totalCrime) ~ shall + log(incarc_rate) + pb1064 +
    pw1064 + pm1029 + pop + avginc + log(density), data = guns_panel,
    model = "within")

Balanced Panel: n = 25, T = 23, N = 575

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-0.49451 -0.10183 -0.00616  0.10462  0.51686

Coefficients:
                  Estimate Std. Error t-value Pr(>|t|)
shallTRUE         -0.09379    0.02387   -3.93  9.6e-05 ***
log(incarc_rate)  -0.05091    0.04146   -1.23  0.22001
pb1064             0.13463    0.04042    3.33  0.00093 ***
pw1064             0.04425    0.00770    5.75  1.5e-08 ***
pm1029            -0.04039    0.01082   -3.73  0.00021 ***
pop                0.03586    0.01529    2.34  0.01941 *
avginc             0.01862    0.00917    2.03  0.04276 *
log(density)      -0.16313    0.10511   -1.55  0.12125
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    17.2
Residual Sum of Squares: 13.4
R-Squared:      0.218
Adj. R-Squared: 0.172
F-statistic: 18.9293 on 8 and 542 DF, p-value: <2e-16
```

Interpretation:

States with shall-issue laws witness a 9.37% crime lesser than those that do not. The pooled OLS model, therefore, exhibits downward bias. The low could be due to endogeneity that is eliminated by the fixed effects entity model.

Model 3 : Fixed Effects model with Entity-fixed and Time-Fixed effects

The Fixed Effects model with Entity-fixed and Time-Fixed effects also includes the time effects by adding the effect of time on the dependent variable totalCrime by including the time dummies. This will capture the effect of time progression in years on the dependent variable totalCrime.

The regression output is given below:

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(totalCrime) ~ shall + log(incarc_rate) + pb1064 +
    pw1064 + pm1029 + pop + avginc + log(density) + year, data = guns_p
    model = "within")

Balanced Panel: n = 25, T = 23, N = 575

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-0.42606 -0.09204 -0.00409  0.07637  0.56421

Coefficients:
                 Estimate Std. Error t-value Pr(>|t|)
shallTRUE        -0.07063    0.02333   -3.03  0.00259 **
log(incarc_rate)  0.03975    0.04313    0.92  0.35714
pb1064            0.00729    0.04847    0.15  0.88056
pw1064           -0.00977    0.01313   -0.74  0.45736
pm1029            0.03759    0.02140    1.76  0.07955 .
pop               0.01806    0.01412    1.28  0.20133
avginc            0.04270    0.01034    4.13  4.2e-05 ***
log(density)     -0.28889    0.10581   -2.73  0.00654 **
year78            0.03413    0.04118    0.83  0.40753
year79            0.12012    0.04221    2.85  0.00460 **
year80            0.16058    0.04328    3.71  0.00023 ***
year81            0.17031    0.04572    3.73  0.00022 ***
year82            0.14331    0.04931    2.91  0.00381 **
year83            0.06712    0.05383    1.25  0.21295
year84            0.05592    0.05961    0.94  0.34862
year85            0.07649    0.06496    1.18  0.23951
year86            0.12962    0.07055    1.84  0.06673 .
```

```
-
year86              0.12962    0.07055    1.84  0.06673 .
year87              0.09499    0.07602    1.25  0.21201
year88              0.13448    0.08228    1.63  0.10277
year89              0.14663    0.08858    1.66  0.09847 .
year90              0.27778    0.11076    2.51  0.01245 *
year91              0.34920    0.11674    2.99  0.00291 **
year92              0.38204    0.12307    3.10  0.00201 **
year93              0.39793    0.12796    3.11  0.00197 **
year94              0.39727    0.13406    2.96  0.00318 **
year95              0.39239    0.14054    2.79  0.00543 **
year96              0.34020    0.14708    2.31  0.02111 *
year97              0.31024    0.15271    2.03  0.04270 *
year98              0.22649    0.15839    1.43  0.15332
year99              0.17121    0.16366    1.05  0.29601
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    17.2
Residual Sum of Squares: 10.6
R-Squared:      0.386
Adj. R-Squared: 0.322
F-statistic: 10.8775 on 30 and 520 DF, p-value: <2e-16
```

Comparing Entity Fixed Model With Time And Entity Fixed Model

From the above output first, we would like to compare the entity fixed model and the time and entity fixed model to do this we will conduct a simple F-Test or chi-squared test in which we will assume that our null hypothesis is that all the coefficient estimates of the time dummies are equal to zero and the alternative that at least one of the coefficients of the time dummies is significant.

If we do not reject the null hypothesis, we would mean that the time effects are irrelevant and hence should not be in our model and hence we would choose the Entity fixed model over the time and entity fixed model.

If we reject the null hypothesis it would mean that at least one of the coefficients of the time dummies is significant and hence we would prefer to add time dummies in our model and choose the time and entity fixed model over the entity fixed model.

Null Hypothesis: H0: $\boldsymbol{\delta 2}$ = $\boldsymbol{\delta 3}$ = $\boldsymbol{\delta 4}$ = $\boldsymbol{\delta 5}$ = $\boldsymbol{\delta 6}$ = $\boldsymbol{\delta 7}$ = $\boldsymbol{\delta 8}$ = $\boldsymbol{\delta 9}$ = $\boldsymbol{\delta 10}$ = $\boldsymbol{\delta 11}$ = $\boldsymbol{\delta 12}$ = $\boldsymbol{\delta 13}$ = $\boldsymbol{\delta 14 = \delta 15 = \delta 16 = \delta 17 = \delta 18 = \delta 19 = \delta 20 = \delta 21 = \delta 22 = \delta 23 = 0}$

Alternative Hypothesis: H1: At least one of them is not equal to zero

The results of the test are as follows:

```
        F test for individual effects

data:  log(totalCrime) ~ shall + log(incarc_rate) + pb1064 + pw1064 +  ...
F = 6, df1 = 22, df2 = 520, p-value <2e-16
alternative hypothesis: significant effects
```

An F-value of 6 and a p-value of practically 0 p-value gives us enough evidence to reject the null hypothesis in favor of the alternate hypothesis. Therefore, we chose the Time and Entity Fixed Entity model.

Is the Random Effects Model Needed to interpret the dataset?

It is only sensible to use the random-effects model for a sample that is randomly selected from a population. But in our case, we are not dealing with a sample dataset, but we have accounted for the whole population in the dataset which is all the 25 states in the US. Thus, we will take Time and Entity Fixed Effects model as our final model.

CONCLUSION

We began our journey exploring the dataset and deriving key insights out of it only to transition into building Pooled OLS, Fixed Effect Entity and Time effects model. After having built the models and interpreted the results, our analysis suggests that implementing shall-issue law does seem to aid in reducing crime