DO SHALL-CARRY LAWS AFFECT CRIME RATES

A Project for BUAN 6312

Ryan Sadovsky, Sujeeth Shetty, Namandeep Shah, Piyush Singh
RPS160030, SSS190004, NXS200002, PXS200044

Introduction

The effect of firearms on wrongdoing in America has set off a great deal of public discussion.

Numerous emphatically accept that state laws empowering residents to convey covered handguns had decreased wrongdoing. As indicated by this view, weapon control laws remove firearms from reputable residents, while would-be hoodlums overlook those leaving potential casualties vulnerable.

Following this view, The National Rifle Association (NRA) and numerous government officials the nation over development the reason for more prominent opportunity to convey firearms.

Accordingly, numerous states in the United States have passed option to-convey laws (otherwise called a will give laws). A Shall-carry law is one that necessitates that administrations issue hid convey handgun grants to any candidate who meets the essential standards. These standards are: the candidate must be a grown-up, have no huge criminal record, and no set of experiences of psychological sickness and effectively complete a course in gun wellbeing preparing (whenever legally necessary). On the off chance that these measures are met, the giving authority has no carefulness in the granting of the licenses, and there is no necessity for the candidate to illustrate "great reason".

Economic Theory

To begin to understand this dataset, means to understand the economic theory associated with this data. For the purposes of this section, we will refer to violent crime rate, robbery rate, and murder rates, collectively as crime rate.

The first variable we examine is the “shall” variable, which is an indicator variable denoting if a state has a shall-carry law in a given year. The economic theory suggests that if a state has an active shall-carry law, then the rates of crime will decrease. This variable may be a big deterrent of crime rates, but it should not be considered as the best or only deterrent. Other variables included in our model could affect crime rates.

Next, we will look at incarceration rates. This variable denotes the rate of incarcerations each year and we would expect crime rates to increase as incarcerations rates increase. While the first intuition we may have is the opposite, the crime rate is positively correlated with the incarcerations rates. This makes sense because as more people are being incarcerated, this means that they are being incarcerated for crimes, thus causing an increase in crime rates.

Next, we have three race and age variables. The first one is the percentage of males between the ages of 10 - 29. We would expect this variable to lead to an increase in crime rates as violent crimes like these are usually by people who tend to have more agility or be cunning. Second, we have the percentage of white males between the ages of 10 - 64. This is an extremely broad variable and is difficult to understand the economic theory with this variable. Similarly, the percentage of black males between the ages of 10 - 64 falls into the same boat. Because the ranges are so large and encompass a large percentage of a state's population, we cannot effectively estimate this variable in our economic theory.

Next, we believe that average income will have a negative effect on crime rates. As the average income goes up, there is less motivation for a crime to take place. Robbery for example, usually is to get possession of value off of one's person, but if the individual has a higher average income, we could expect for crime rates to drop.

Finally, we have two population variables: density and state population. We expect both of these variables to lead to an increase in the crime rates. For density, when more people live in an area, there is a higher probability of somebody in that area to commit a crime. Highly dense populations usually see a higher rate of crime compared to an area where the people are more spread out. Similarly, a state's population, while the individuals are more widespread, the higher population means that more people in that state are able to commit crimes.

Hypothesis

Do shall-issues law reduce crime-or not?

To test our hypothesis we examine pooled OLS models, fixed effect models without time fixed effects, time fixed effects models, and random effects models. From these models, we will determine which variables should be included and the effect they have on crime rates, and also determine which model is best and make a formal decision about our hypothesis based on that model

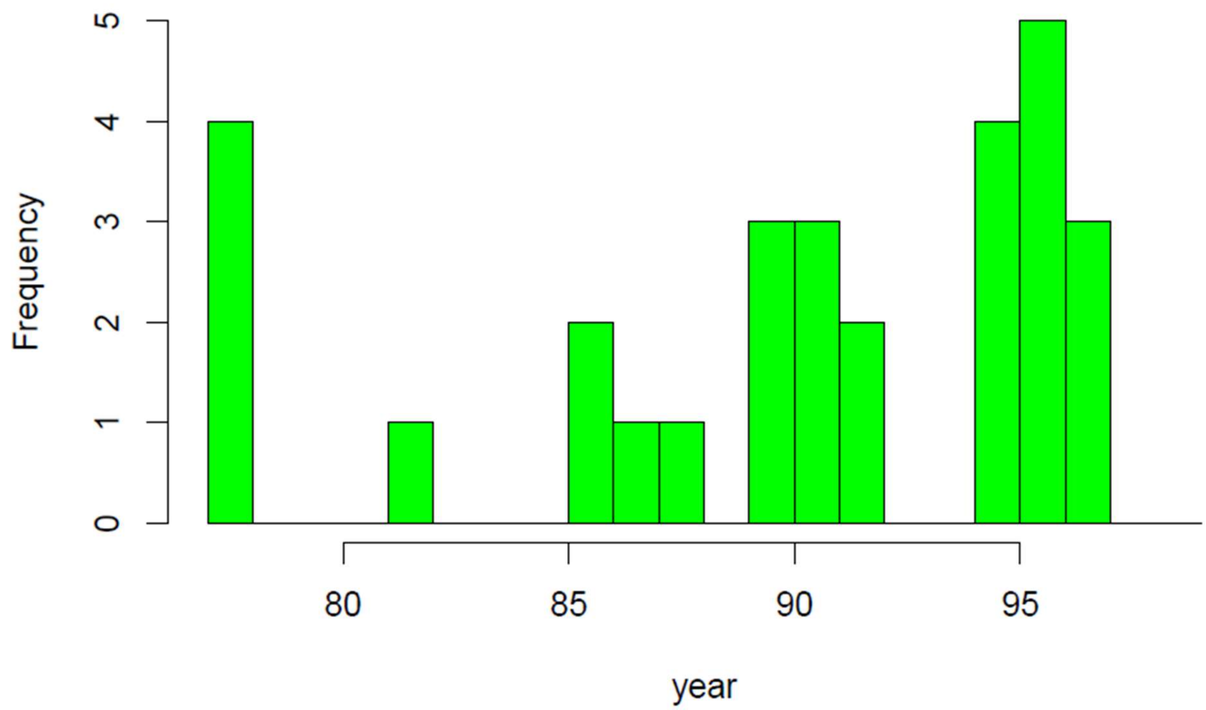
Data

1. Guns is a balanced panel data on 50 US states, plus the District of Columbia (for a total of 51 "states"), by year for 1977 – 1999.
2. Each observation is a given state in a given year. There are a total of 51 states × 23 years = 1173 observations.
3. We are going to investigate the effect of the introduction of shall-carry laws on 3 variables i.e 'vio', 'mur', and' rob'.

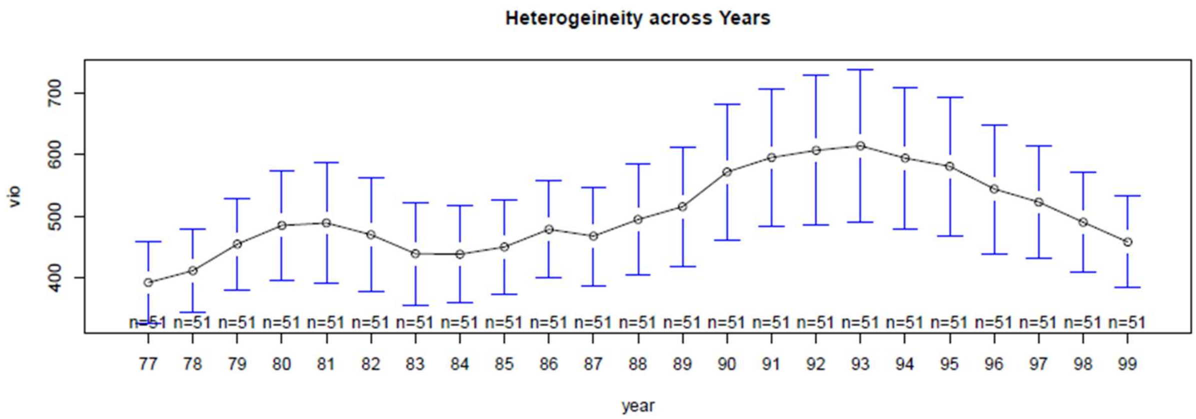
Variable	Definition
vio	violent crime rate (incidents per 100,000 members of the population)
rob	robbery rate (incidents per 100,000)
mur	murder rate (incidents per 100,000)
shall	= 1 if the state has a shall-carry law in effect in that year = 0 otherwise
incarc_rate	incarceration rate in the state in 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)

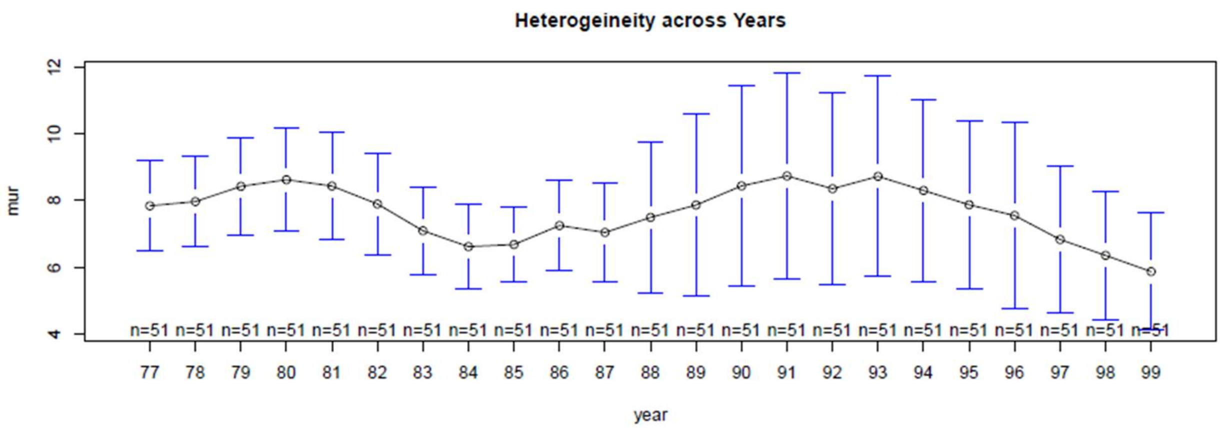
Exploratory Data Analysis

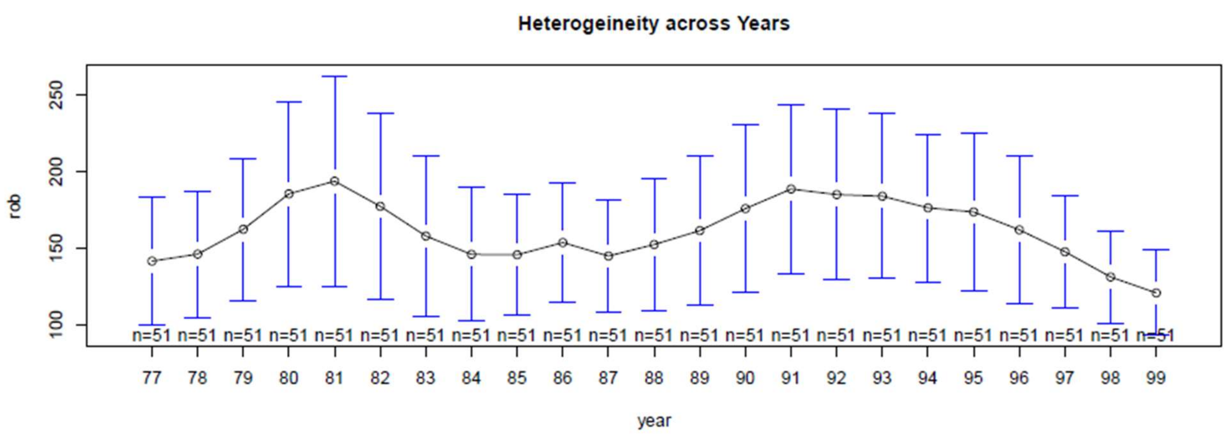
The right-to-carry shall law was introduced in different years in different states. Out of 51, only 29 states had law effective in the observed time period. 17 out of the 29 states implemented shall laws after 1990



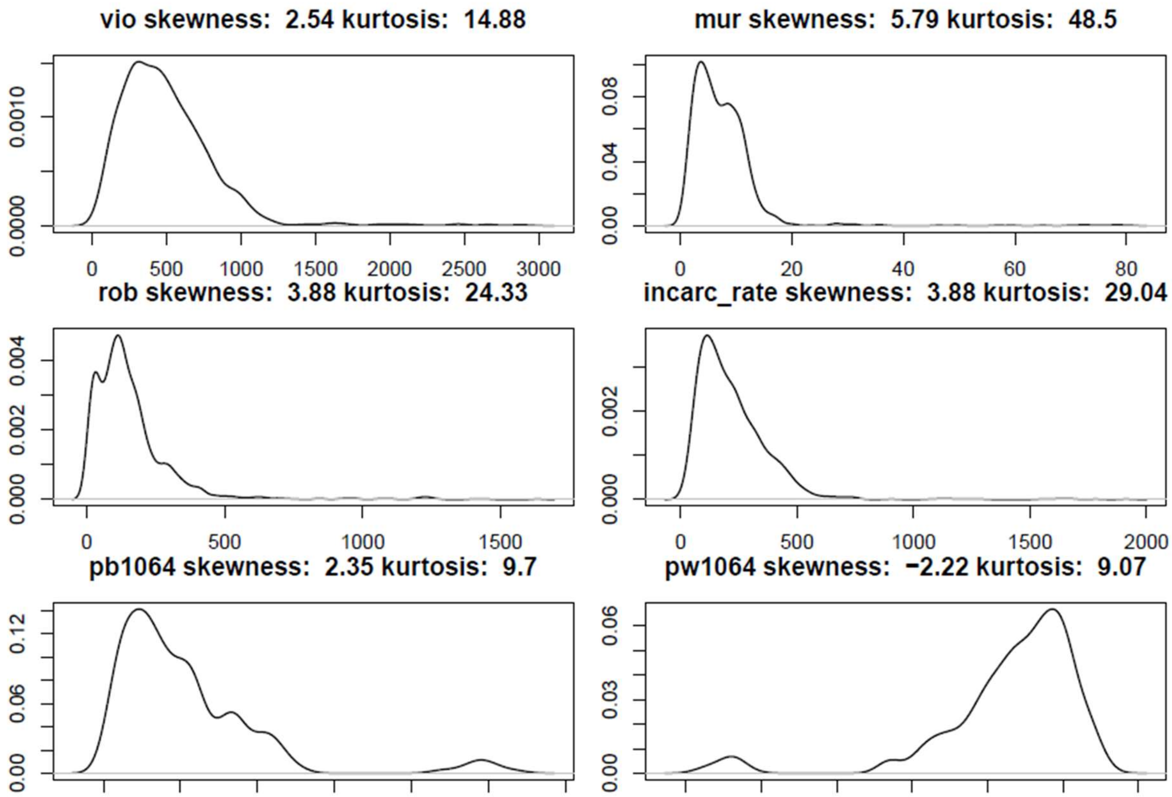
The below graph shows the average vio/mur/rob rate for each year.

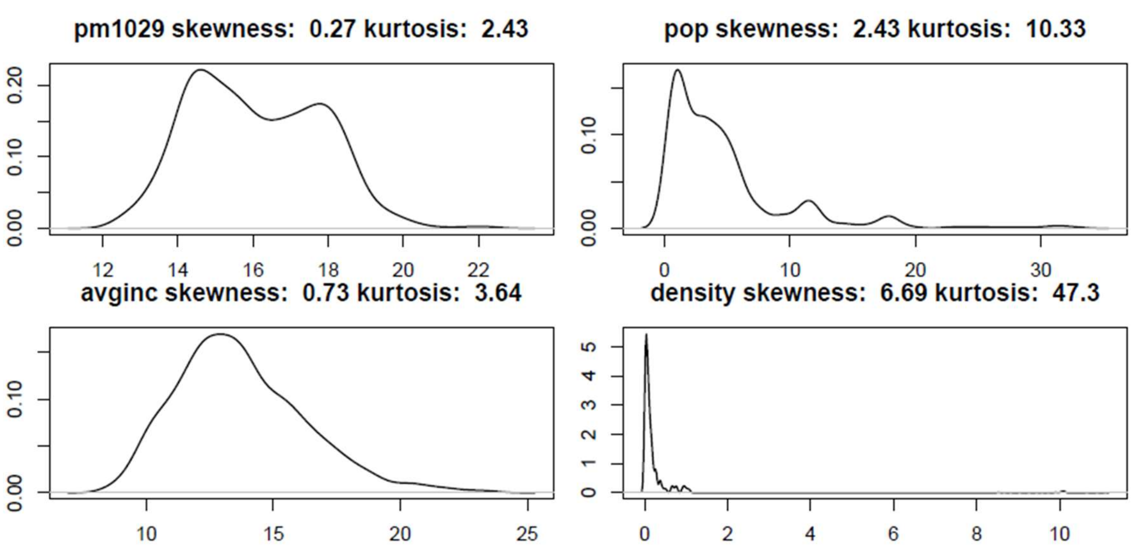




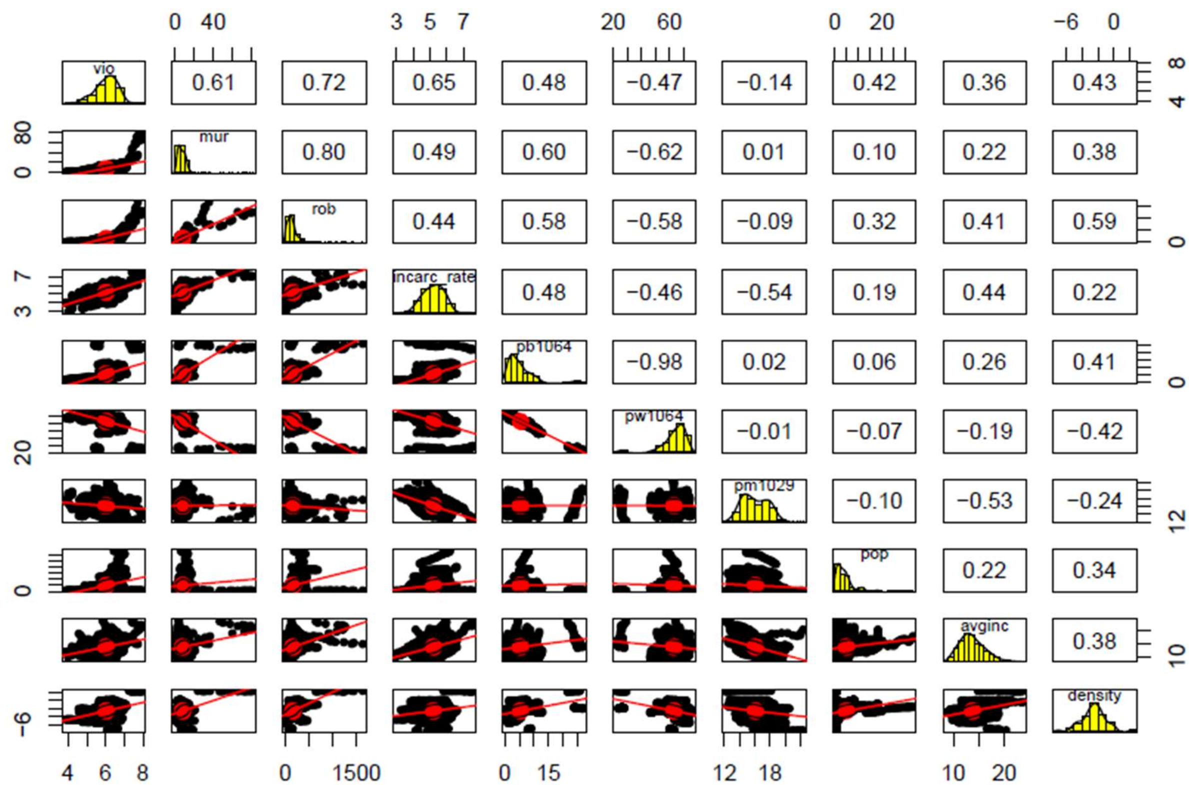


The normality of each variable is shown below using a density plot. Violent crime rate, Incarceration rate and density of population have high skewness (above 2.5). These three variables will be transformed using logarithmic function.





From the correlation plot we can see that pb1064 (percentage of state population that is black in age 10–64) and pw1064(percentage of state population that is white in age 10–64) are highly negatively correlated (-0.98). Including these variables might lead to inflated standard error.



Model

After doing the log transformation of variables to counter skewness .We are going to run 4 models each to check the effect of introduction of shall laws on 3 variables i.e 'vio' , 'mur' and 'rob'. Four models will be

1. Pooled-OLS model
2. Fixed effect model
3. Fixed effect model with time
4. Random effect model

To begin, we created the model: Ln(Vio) = Ln(Incarc_rate) + pb1064 + pm1029 + pop + avginc + Ln(density) + shall + pw1064. We created a pooled model from this regression and received the following result.

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)       0.1816538  0.4902108  0.3706 0.7110307
log(incarc_rate)  0.6935672  0.0252298 27.4900 < 2.2e-16 ***
pb1064            0.0033125  0.0143860  0.2303 0.8179308
pm1029            0.1167641  0.0102156 11.4300 < 2.2e-16 ***
pop               0.0240749  0.0023009 10.4633 < 2.2e-16 ***
avginc            0.0232989  0.0063738  3.6554 0.0002682 ***
log(density)      0.0928883  0.0089614 10.3653 < 2.2e-16 ***
shall1           -0.2826839  0.0283135 -9.9841 < 2.2e-16 ***
pw1064            0.0033576  0.0070293  0.4777 0.6329816
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 160.62
R-Squared:      0.67128
Adj. R-Squared: 0.66902
F-statistic: 297.126 on 8 and 1164 DF, p-value: < 2.22e-16
```

Based on the above results, when a state has a shall carry law, the coefficient is -.283, which is approximately a 28.3% decrease in violent crime rate for that state. The actual effect of the shall carry law per state is a 24.6% decrease in violent crime rates. This regression shows that this result is statistically significant. Additionally, this regression output tells us that both pb1064 and pw1064 are insignificant. To test if they are jointly significant, we ran an F-test and have concluded that these variables are not significant and should be removed from the model. Our new model is now: Ln(Vio) = Ln(Incarc_rate) + pm1029 + pop + avginc + Ln(density) + shall. Below is the output of this regression

```
                   Estimate Std. Error t value  Pr(>|t|)
(Intercept)       0.5193308  0.7026614  0.7391 0.4600004
log(incarc_rate)  0.6781482  0.0666298 10.1779 < 2.2e-16 ***
pm1029            0.1134168  0.0227080  4.9946 6.796e-07 ***
pop               0.0245819  0.0074874  3.2831 0.0010571 **
avginc            0.0239844  0.0163878  1.4635 0.1435869
log(density)      0.0880118  0.0270546  3.2531 0.0011742 **
shall1           -0.2780539  0.0779611 -3.5666 0.0003763 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The above result is our new regression output. After omitting these variables, shall-carry laws are still significant and lead to an approximate reduction in crime rates by 27.8% and an exact reduction in crime rates by 24.27%

Next, we will observe the original model stated using fixed effects and ignoring time effects. Below is the regression output

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.0672299  0.0282092 -2.3833  0.017327 *
pb1064            0.0952893  0.0150322  6.3390 3.352e-10 ***
pm1029           -0.0690675  0.0083143 -8.3071 2.821e-16 ***
pop               0.0243860  0.0092824  2.6271  0.008729 **
avginc           -0.0041476  0.0057273 -0.7242  0.469107
log(density)     -0.2518321  0.0859535 -2.9299  0.003460 **
shall1           -0.0379065  0.0189886 -1.9963  0.046147 *
pw1064            0.0428067  0.0052073  8.2205 5.591e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

From this regression output, we see that avginc is not significant, and thus we should remove it from the model. Our new regression out is shown below

```
Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.0726069  0.0272087 -2.6685  0.007729 **
pb1064            0.0940313  0.0149283  6.2989 4.307e-10 ***
pm1029           -0.0672520  0.0079256 -8.4854 < 2.2e-16 ***
pop               0.0241646  0.0092753  2.6052  0.009303 **
log(density)     -0.2503523  0.0859108 -2.9141  0.003638 **
shall1           -0.0380101  0.0189840 -2.0022  0.045503 *
pw1064            0.0425889  0.0051975  8.1941 6.872e-16 ***
```

With this new fixed effect regression, we see that all variables are significant and we can proceed with our model testing. Additionally, shall carry law are still significant and alpha = 5% and the approximate effect of these laws per state is a 3.8% decrease in violent crime rates, while the exact effect is 3.73% decrease in crime rates. Next, we will run a model again using all variables and running it with fixed effects and time fixed effects. Below are the results of the regression output.

```
Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)    
log(incarc_rate) -0.1042006  0.0281708 -3.6989 0.0002273 ***
pb1064           -0.0116159  0.0196878 -0.5900 0.5553079    
pm1029            0.0790354  0.0154122  5.1281 3.461e-07 ***
pop               0.0060215  0.0083075  0.7248 0.4687083    
avginc            0.0018515  0.0062919  0.2943 0.7686099    
log(density)     -0.2539256  0.0768528 -3.3041 0.0009839 ***
shall0            0.0280294  0.0172992  1.6203 0.1054622    
pw1064           -0.0012751  0.0076177 -0.1674 0.8670976    
factor(year)78    0.0676702  0.0280068  2.4162 0.0158464 *  
factor(year)79    0.1865317  0.0286830  6.5032 1.194e-10 ***
factor(year)80    0.2485785  0.0292264  8.5053 < 2.2e-16 ***
factor(year)81    0.2569276  0.0304912  8.4263 < 2.2e-16 ***
factor(year)82    0.2505044  0.0327855  7.6407 4.710e-14 ***
factor(year)83    0.2292094  0.0358749  6.3891 2.465e-10 ***
factor(year)84    0.2715517  0.0397885  6.8249 1.456e-11 ***
factor(year)85    0.3302088  0.0435107  7.5891 6.881e-14 ***
factor(year)86    0.4184033  0.0478227  8.7490 < 2.2e-16 ***
factor(year)87    0.4274345  0.0521690  8.1933 7.056e-16 ***
factor(year)88    0.4992313  0.0569334  8.7687 < 2.2e-16 ***
factor(year)89    0.5644762  0.0613829  9.1960 < 2.2e-16 ***
factor(year)90    0.7010563  0.0743982  9.4230 < 2.2e-16 ***
factor(year)91    0.7656107  0.0780946  9.8036 < 2.2e-16 ***
factor(year)92    0.8085043  0.0824750  9.8030 < 2.2e-16 ***
factor(year)93    0.8406784  0.0856934  9.8103 < 2.2e-16 ***
factor(year)94    0.8368898  0.0895086  9.3498 < 2.2e-16 ***
factor(year)95    0.8428252  0.0933387  9.0298 < 2.2e-16 ***
factor(year)96    0.7985925  0.0970704  8.2269 5.418e-16 ***
factor(year)97    0.7878690  0.1006015  7.8316 1.135e-14 ***
factor(year)98    0.7426847  0.1046289  7.0983 2.270e-12 ***
factor(year)99    0.6931981  0.1081344  6.4105 2.154e-10 ***
```

From this regression, we see that all of the time indicator variables are significant, they shall carry law variable is no longer significant even at alpha = 10%, and that pb1064, pop, avginc, and pw1064 are no longer significant. To test the joint significance of the last four variables mentioned, we will conduct an F-test. This F-test produces a F-statistic of 1.2762 and a p-value of .8654 and concludes that these variables are not jointly significant and should be removed from the model. Running this new regression, below are the regression outputs

```
Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.100500   0.027696 -3.6287 0.0002980 ***
pm1029            0.076889   0.010840  7.0930 2.350e-12 ***
log(density)     -0.238238   0.066390 -3.5885 0.0003473 ***
shall0            0.028818   0.016815  1.7138 0.0868507 .
factor(year)78    0.067671   0.027600  2.4519 0.0143670 *
factor(year)79    0.185452   0.027945  6.6362 5.049e-11 ***
factor(year)80    0.245724   0.028304  8.6816 < 2.2e-16 ***
factor(year)81    0.253555   0.028856  8.7869 < 2.2e-16 ***
factor(year)82    0.245901   0.030358  8.1000 1.454e-15 ***
factor(year)83    0.224037   0.032424  6.9096 8.229e-12 ***
factor(year)84    0.266666   0.034426  7.7462 2.148e-14 ***
factor(year)85    0.325099   0.036616  8.8785 < 2.2e-16 ***
factor(year)86    0.413072   0.039360 10.4947 < 2.2e-16 ***
factor(year)87    0.421620   0.042133 10.0069 < 2.2e-16 ***
factor(year)88    0.492966   0.044943 10.9687 < 2.2e-16 ***
factor(year)89    0.557756   0.047630 11.7103 < 2.2e-16 ***
factor(year)90    0.690794   0.050965 13.5543 < 2.2e-16 ***
factor(year)91    0.754124   0.053891 13.9934 < 2.2e-16 ***
factor(year)92    0.796624   0.056339 14.1399 < 2.2e-16 ***
factor(year)93    0.828054   0.058362 14.1883 < 2.2e-16 ***
factor(year)94    0.823881   0.060380 13.6449 < 2.2e-16 ***
factor(year)95    0.829268   0.062673 13.2316 < 2.2e-16 ***
factor(year)96    0.784634   0.064729 12.1219 < 2.2e-16 ***
factor(year)97    0.773790   0.066283 11.6740 < 2.2e-16 ***
factor(year)98    0.728803   0.067552 10.7888 < 2.2e-16 ***
factor(year)99    0.678991   0.068681  9.8862 < 2.2e-16 ***
```

Even after removing those variables, shall carry laws are now significant at alpha = 10%, but not at alpha = 5%. Below is the new model with the removed variables.

Now that we have these two models, we can test to see which fixed effect model is better for our interpretations. To do this, we will run a F-test for individual effects where our null hypothesis will be that no time fixed effect is needed. This test produces a F-statistic of 20.228 and a p-value that is practically 0, and thus we will conclude that we will need a model with time fixed effects.

```
data:  log(vio) ~ log(incarc_rate) + pm1029 + log(density) + shall +  ...
F = 20.228, df1 = 19, df2 = 1096, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Finally, we will observe the coefficients using the Random Effects Model. Below is the regression output.

```
Coefficients:
                    Estimate Std. Error z-value  Pr(>|z|)
(Intercept)        3.7089892  0.4113808  9.0160 < 2.2e-16 ***
log(incarc_rate)   0.0011089  0.0283521  0.0391  0.968800
pb1064             0.1117660  0.0129132  8.6552 < 2.2e-16 ***
pm1029            -0.0407458  0.0080205 -5.0802  3.77e-07 ***
pop                0.0217939  0.0063425  3.4362  0.000590 ***
avginc            -0.0062443  0.0058167 -1.0735  0.283037
log(density)       0.0611245  0.0300360  2.0350  0.041847 *
shall1            -0.0688798  0.0192294 -3.5820  0.000341 ***
pw1064             0.0401063  0.0052927  7.5776  3.52e-14 ***
---
```

From this regression output, we see that avginc and log(incarc_rate) is not significant. To identify the best model among Time Fixed Effect and Random Effect we performed Hausman test. This test produced chi-square of 162.56 and p-value practically close to zero, and thus we will conclude that we will need a Time Fixed Effect Model.

```
 Hausman Test

data:  log(vio) ~ log(incarc_rate) + pm1029 + log(density) + shall +  ...
chisq = 162.56, df = 3, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

We performed similar experiment with Murder Rate & Robbery Rate as target variable and found out Time Fixed Effect regression to be a better model. The regression output is given below.

Murder Rate:

```
Coefficients: (1 dropped because of singularities)
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.082209   0.042195 -1.9483 0.0516338 .
pm1029            0.051621   0.016515  3.1257 0.0018205 **
log(density)     -0.467600   0.101146 -4.6230 4.231e-06 ***
shall0            0.046687   0.025618  1.8224 0.0686678 .
factor(year)78    0.033460   0.042048  0.7958 0.4263494
factor(year)79    0.100386   0.042575  2.3579 0.0185559 *
factor(year)80    0.119890   0.043122  2.7803 0.0055243 **
factor(year)81    0.140007   0.043962  3.1847 0.0014899 **
factor(year)82    0.065429   0.046251  1.4146 0.1574571
factor(year)83    0.030116   0.049399  0.6097 0.5422165
factor(year)84   -0.038162   0.052448 -0.7276 0.4669984
factor(year)85    0.028474   0.055786  0.5104 0.6098620
factor(year)86    0.122321   0.059965  2.0399 0.0416037 *
factor(year)87    0.120032   0.064190  1.8699 0.0617578 .
factor(year)88    0.151265   0.068472  2.2092 0.0273695 *
factor(year)89    0.172984   0.072564  2.3839 0.0173010 *
factor(year)90    0.256439   0.077646  3.3027 0.0009885 ***
factor(year)91    0.299166   0.082104  3.6437 0.0002813 ***
factor(year)92    0.286196   0.085833  3.3343 0.0008836 ***
factor(year)93    0.380293   0.088915  4.2770 2.059e-05 ***
factor(year)94    0.288302   0.091990  3.1341 0.0017698 **
factor(year)95    0.318812   0.095484  3.3389 0.0008694 ***
factor(year)96    0.271743   0.098615  2.7556 0.0059556 **
factor(year)97    0.193962   0.100984  1.9207 0.0550246 .
factor(year)98    0.169373   0.102916  1.6457 0.1001037
factor(year)99    0.123646   0.104636  1.1817 0.2375896
```

Robbery Rate:

```
Coefficients: (1 dropped because of singularities)
                 Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.207905   0.038150 -5.4497 6.228e-08 ***
pm1029            0.092819   0.014932  6.2162 7.226e-10 ***
log(density)      0.116640   0.091448  1.2755 0.2024103
shall0            0.011098   0.023162  0.4791 0.6319354
factor(year)78    0.045934   0.038017  1.2083 0.2272075
factor(year)79    0.164413   0.038493  4.2712 2.113e-05 ***
factor(year)80    0.270644   0.038987  6.9418 6.615e-12 ***
factor(year)81    0.307505   0.039747  7.7365 2.309e-14 ***
factor(year)82    0.272876   0.041817  6.5255 1.033e-10 ***
factor(year)83    0.203907   0.044662  4.5655 5.546e-06 ***
factor(year)84    0.181675   0.047419  3.8313 0.0001347 ***
factor(year)85    0.230308   0.050437  4.5663 5.527e-06 ***
factor(year)86    0.326436   0.054216  6.0210 2.362e-09 ***
factor(year)87    0.310686   0.058036  5.3533 1.051e-07 ***
factor(year)88    0.362667   0.061907  5.8583 6.178e-09 ***
factor(year)89    0.435409   0.065607  6.6366 5.036e-11 ***
factor(year)90    0.538119   0.070201  7.6654 3.914e-14 ***
factor(year)91    0.665258   0.074232  8.9619 < 2.2e-16 ***
factor(year)92    0.678621   0.077603  8.7447 < 2.2e-16 ***
factor(year)93    0.704287   0.080390  8.7609 < 2.2e-16 ***
factor(year)94    0.730898   0.083170  8.7880 < 2.2e-16 ***
factor(year)95    0.749439   0.086329  8.6812 < 2.2e-16 ***
factor(year)96    0.708814   0.089160  7.9499 4.615e-15 ***
factor(year)97    0.657588   0.091301  7.2024 1.098e-12 ***
factor(year)98    0.581167   0.093049  6.2458 6.020e-10 ***
factor(year)99    0.516994   0.094604  5.4648 5.733e-08 ***
```

Conclusion

Based on all of the analysis and testing of different models that we have conducted, we will finalize our model using the time fixed effects. From that regression output, we know that shall-carry laws approximately increase violent crime rates by 2.8% and will exactly increase violent crime rates by 2.84%. Robbery rate will increase by 1.1% and Murder rate will increase by 4.66 % by introduction of shall-carry laws. From all of the analysis that we have performed and various models we have created and tested, we can formally conclude that shall-carry laws do not lower the rates for violent crimes , murder rate and robbery rate.

Limitations

While this conclusion does not line up with what we stated in our portion about the economic theory, outside factors that are captured in the error term could be what led us to this conclusion. Attitudes about shall-carry laws and gun laws in general vary from state-to-state, thus adding in a variable that we cannot measure that is captured in the error term. Also, from an example we learned in class, looking at lawsuits per state in a given year could serve as a valuable instrumental variable. But in conclusion, our analysis has shown that we do not shall-carry laws do not lead to a decrease in crime rates (violent, murder, and robbery).