Econometrics Project: Shall Laws and Violence

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Executive Summary:

The goal of this analysis is to determine what effects shall-issue laws have on the amount of violence in 50 US states and DC. We try to delve further on the matter. This is a descriptive Data Model analyzed in R which talks in depth about whether shall issue laws have any impact on criminality or does it have any positive or negative correlation with Violence in the 50 US states and the District of Columbia. We aim to analyze the impact of this relationship. Some pertinent questions emerged and this study is an attempt to tell the story behind those. Initially, it was essential to consolidate an economic theory to base our model on. Efforts were made to understand the relationship between the dependent variable and the independent variables. While initially studying the data, we found that the data contained 56 Stateids that needed to be grouped into 51. We invested efforts into trying to understand the Data Model Type and then further delved to see if the data was balanced or unbalanced by nature.

As we have already established, this study aims to gain a deeper understanding of the dataset by analyzing it further. Initial analysis was aimed at establishing relationship between variables and The Layman could see that data had no missing values. Attempts were made to decipher the set of explanatory variables and how they can help us reach our end goal of showing the impact of these laws on violence. We then moved further to decide which Model type works the best for our analysis. Given the Non Randomness of our model, a fixed effects model was chosen. However, on further scrutinizing, we realize that further alterations needed to be made. A series of models were made which are discussed later, followed by a couple of iterations which led us to a new finding which forms the basis of our study. Once the model was developed, we moved further down to analyze the impact of these variables and interpret the results.

Throughout the process, the objective has been to come up with the most astute economic theory and the most pragmatic economic solution. We have tried to address some of the key problems any data model encounters and worked our way around our limitations. While performing the initial analysis, it was clear that this is a panel data type and has data balance in it without any missing values. Violence, Murder and Robbery had a high correlation amongst themselves. We also try to talk in depth about lesser but impactful correlation between some other variables. We then try to understand the nature of the dataset. To do that, we try and perform hypothesis testing, search for possibly omitted variables(Those variables which can have some potential information useful in the analysis that have not been directly included within the Model) and look for collinearity where various methods to test collinearity along with their solutions and proposed outcomes. We also try to figure out the Endogeneity where we test if the Model has time effects or Entity effects and outliers within the dataset to check for what particular states have values that can differ from the general analysis given their Outlying values.

All these steps have been successfully performed with a set of predefined objectives. All these efforts were made in order to successfully decode the key trends within the dataset and to analyze it better. Once the initial analytical screening was dealt with, we moved further and beyond to design the Data Model. Our data model couldn't be built until at least 8 previous models that have been discussed were proposed and rejected. As we will later see, all these models had an outcome which helped us understand the dataset better. These iterations thus proved beneficial while designing the ultimate Data Model which has been depicted in Fig 2.20.

Initial Analysis:

1. **Initial analysis & understanding the data:**
    a. **Cleaning data:**
        i. **Panel data type:** It is a wide-wide panel data as we have 51 entities and 23 years of observations.
        ii. **Data balance:** The data is balanced as we have 23 observations per each entity.
        iii. **Missing data:** The data has no missing values.
    b. **Initial understanding of the data:**
        i. **Correlation between variables:**
            1. Clear correlation over 80% between violence, murder and robbery, which does make sense but we need to take care when modeling as we will have multicollinearity issues.

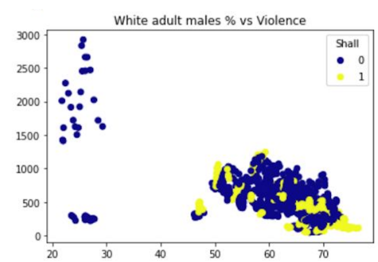
2. There is a moderate correlation between violence and black and white distribution.
3. There is an extreme correlation between black and white distribution which will definitely add multicollinearity issues to our data.
4. Density has moderate correlation with violence, so it is worth studying.

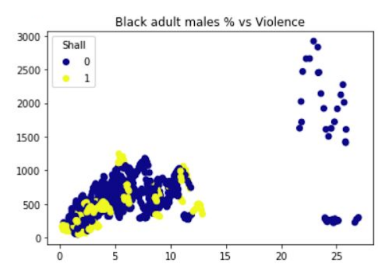
ii. Initial hypothesis on the data before modelling:

1. Relationship between application of Shall and crime indicators:

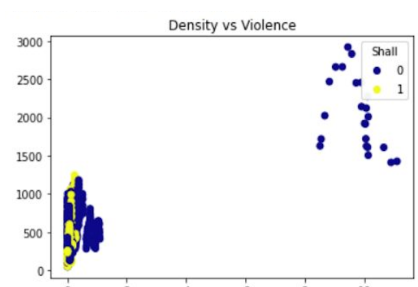
	Violence	**Robbery**	**Murdur**
Shall intact	381	5.28	97.9
No-Shall period	542	8.43	182.34

2. Relationship between application of Shall and % of black and white adult males: minority has the biggest impact here.





3. Relationship between density and violence:
   As we can see here that the density plays a major impact on violence rate as compared to whether shall is intact or not.



c. **Possible omitted variables:**

What other information might be useful in performing this analysis?

i. May be levels of illegal ownership of guns before the law as this would impact the entities heterogeneity.

d. Collinearity:

1. As mentioned before that there is a high probability that a couple of variables may have strong collinearity, here are the steps for figuring that out and treatment:
2. **Testing for multicollinearity:**

   We have used **VIF,** to show how much those variables are collinear and would significantly impact our estimation standard errors and confidence intervals.
3. **Results:**

   As we can see that we have the following variables are collinear:
   - Mur and Rob.
   - Pb1064 and pw1064.

	VIF Factor	Variable
0	5.918303	mur
1	5.997456	rob
2	4.055680	incarc_rate
3	42.642767	pb1064
4	42.924495	pw1064
5	2.513261	pm1029
6	1.702026	pop
7	2.655785	avginc
8	4.230548	density
9	1.278073	shall

4. **Treatment:**

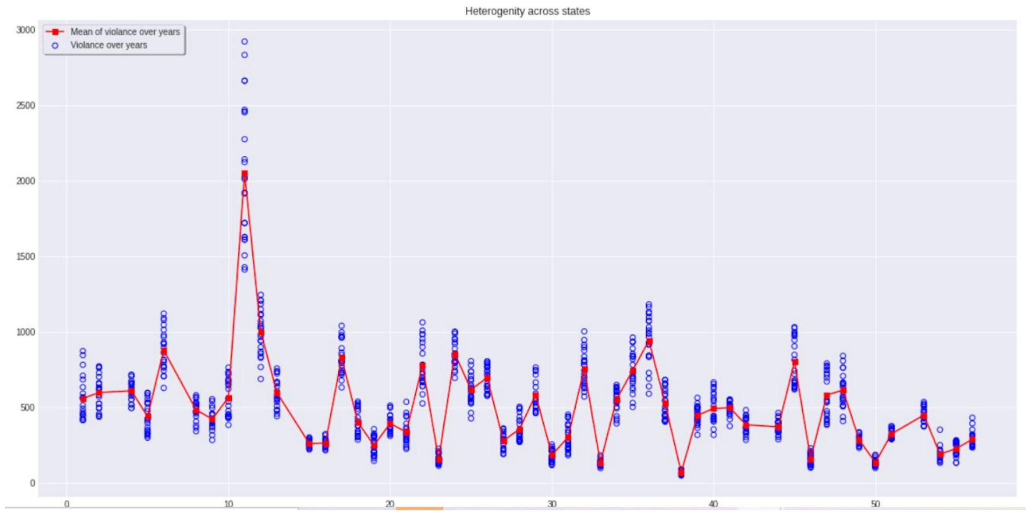
   We have tried treatment by centering variables around the mean, but this happened as a result that they may be related by a polynomial relationship which would treat the multicollinear present in the data.
5. **Recommendations:**
   - We can drop either mur or rob from the exogenous variables.
   - We can add indicator variables for black majority or white majority with a reference group being the other group.

e. Endogeneity:

We are trying to observe whether the data has time effects or entity effects:

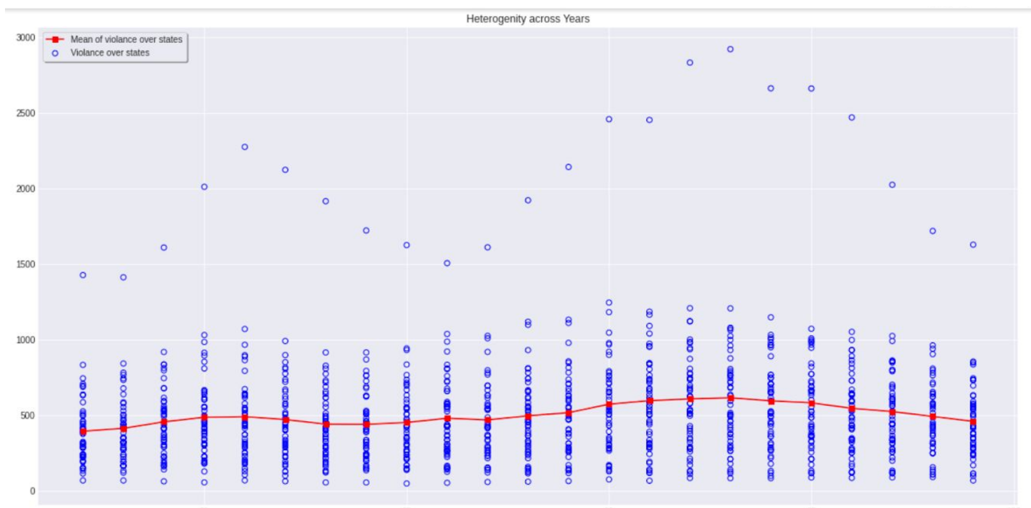
- **Plot for differences over states:**

It is clear that there are entity effects between states.



- **Plot for differences over years:**

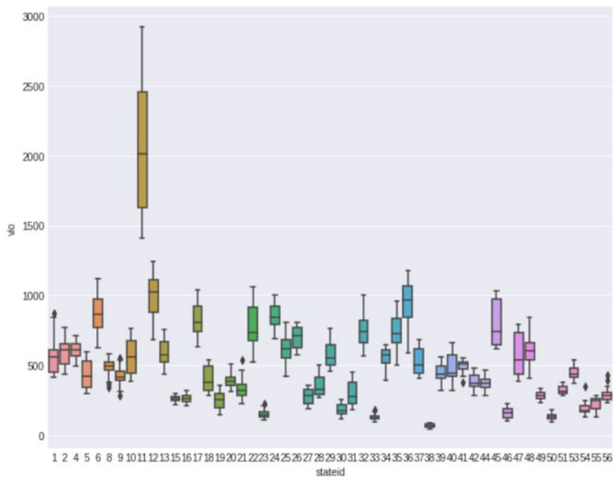
  It is clear that differences over years are not that much different from year to year.



f. Outliers:

We are observing outliers not because it would affect our modeling performance but because it may affect our interpretation for few insights.

As we can see that state 11 is an extreme outlier when it comes to violence.



<u>Model Specification:</u>

Fixed Effects Variables:

The first step in the process of developing an econometric model that explains the effects from shall laws on the violence rate in the US is to understand the econometric theory, and the most appropriate corresponding model to utilize in our analysis. Accordingly, our group decided to utilize the fixed effects model. First, the fixed effects model is more preferred when the dataset is composed of non-randomly selected groups, like the 50 US states and DC. These groups were predetermined, and that means that the effects from unknown omitted variables that may affect the analysis of those groups cannot be randomized away by random sampling. Therefore, the fixed effects model is most appropriate as it is designed to account for unknown variables that may affect analysis, but that cannot be randomized away. Although the random effects model is not the most efficient method of analysis, unlike the random effects model, it can deliver more accurate analysis under this context. Specifically, the fixed effects model is best able to control for omitted factors that may be unique to a certain state, or a certain year. Some omitted variables are constant effects for any given state, and the stateid dummy variables in the model are able to control for those. Also, there may be some trends that are constant across all entities, but that vary by year, and the year dummy variables are able to control for omitted variables such as those. The first stateid and year dummy variables were omitted to avoid exact collinearity.

After the general form of the model was decided upon, more analysis was needed to determine which variables were most relevant in explaining the violence rate. A series of models were made, along with corresponding f-tests, to determine which variables should be considered in the final model. Those models included a reduced model with only a simple intercept, another with only the standalone shall variable, the initial dummy variables, highly correlated explanatory variables, quadratic variables, and interaction variables. These models were created iteratively until a final model was obtained with a combination of all of the above models. The reasoning and econometric theory behind each iteration will be explained. The final model was obtained using a stepping regression algorithm which adds variables based on which variables minimize AIC and BIC, and that maximizes adjusted R-squared. The specifics will be further discussed below.

The first model was a single variable model with the shall dummy variable as a standalone variable. The results of the first model can be seen in Table 2.1, and it seems that shall is a very significant variable by itself. The results show that states who have implemented shall laws have 161 fewer violent crimes per 100,000, and the results are significant at a 1% alpha level. This model also has an overall f-statistic of 52, which means that that variable alone is able to explain the data extremely well. So, according to this simple model, it seems that shall laws alone do in fact contribute significantly to reducing violent crime rates, but we know this is not the whole story. There are multiple other variables that could be correlated with the existence of shall laws, and this could obscure the true effects of shall laws.

Another model was made which only contained the other explanatory variables mur, rob, incarc_rate, pb1064, pw1064, pm1029, pop, avginc, density, and that did not include any dummy variables. The regression results from this full model including the rest of the explanatory variables in the original dataset can be seen in Table 2.2. This full model was not a fixed effects model. An f-test was performed comparing both of these models to see if the additional variables have any explanatory value on predicting the violent crime rate, and the results from that ANOVA-based f-test can be seen in Table 2.3. The null hypothesis was that none of the additional variables have explanatory value, and the alternative hypothesis was that at least one of them did. Per the results in Table 2.3, it is evident that at least one of these variables do, so we would reject the null. This conclusion makes sense due to the fact that the variables density, pm1029, incarc_rate, rob, and mur were all significant results in the regression for the full model in table 2.2. So, we will consider these variables in our final model.

Next, tests were performed to determine if any of the highly correlated variables, namely rob, mur, and incarc_rate have any explanatory value, or if they are merely repetitive information in the model which reduces the quality of results due to their high correlation with the dependent variable and with each other. Each of these variables were highly correlated with vio around or above .5 and were correlated with each other at or above a level of .2. So, the reduced model was made without these variables included in the regression and the full model was made with them. The reduced model can be seen in Table 2.5, and the full model is the same as the model in Table 2.2. An f-test was performed comparing both of these models, and the results from that f-test can be seen in Table 2.6. The results of this f-test conclude that those highly correlated variables are not just a repeat of existing information and that at least one of them have explanatory value because the f-test was very conclusive with an f-statistic of 1038. So, these variables will also be considered in the final model.

An important next step in our analysis included the creation of fixed effects models, and corresponding tests to determine if those variables have significant explanatory value. The full model in Table 2.7 includes all of the stateid dummy variables which account for omitted variables with constant effects within each individual state entity that may impact the results of the analysis. The reduced model can be seen in Table 2.2. The null hypothesis was that the stateid dummy variables had no explanatory value, and the alternative hypothesis was that at least one of them do have explanatory value. The results of the f-test comparing the two models can be seen in Table 2.8. There is strong evidence (f-stat of 65.9) that those indicator variables have strong explanatory value, so they will be included in the final model specification. This f-test is important for econometric theory in many ways as the stateid dummy variables account for fixed within entity effects. This model concludes that there are in fact constant effects within each state that are omitted which are relevant predictors of violent crime rates. An example of that may be the presence, or absence, of gangs in certain states. If there are many gangs in a certain state, that could contribute to violent crime. Assuming those gangs have a stronger foothold in that state, that could be a fixed effect which always contributes to that state having higher violent crime rates, for example. So, our test confirms that there are some such variables omitted from the dataset which are significant, and the fixed effects model is appropriate.

Another fixed effects variable considered in our analysis is yearly fixed effect variables. These variables differ from having fixed effects variables for each state entity in that they cannot account for within entity variation, but they can account for omitted variables which are constant across entities but that vary over time. So, these yearly fixed effects variables account for the effects of omitted variables like increased surveillance capabilities by police forces, the NSA, and the FBI, for example. If the FBI had a new breakthrough technology using surveillance which allowed them to predict and respond better to violent criminals, then that could reduce crime rates nationwide. That kind of breakthrough could affect every state almost the same, but would change year to year. There are many other possible variables that could be seen as having consistent effects across all state entities, but that vary over time, and so that is why each year was given its own fixed effect variable. The results of the yearly fixed effects model can be seen in Table 2.9, and the reduced model it is being compared with can be seen in Table 2.2. The f-test in Table 2.10 produced an f-statistic of 3.9 which is significant at a 1% alpha level, and indicates that there are in fact some yearly fixed effects which affect all state entities the same, but that vary each year. These variables will also be considered in the final model.

To follow up on the information in the last two paragraphs, a model containing both the yearly fixed effects and the stateid fixed effects variables was created to determine if the shall variable was still a valid predictor of the violent crime rate. This model with both kinds of fixed effects variables can be seen in Table 2.11. Per the results, shall is still a valid predictor of violent crime rates even at a 1% significance level. This is very strong evidence that shall-issue laws do help reduce the crime rate by 19 cases out of 100,000 on average. However, this is an incomplete analysis of the effects from shall-issue laws because this model ignores the possibility of interactions between explanatory values as well as the fact that there may be some non-linear relationships between different explanatory variables and the violent crime rate. So, the next phase of this analysis involves determining if either quadratic or interaction variables should also be considered.

Additional Variables:

Non-linear variables are the subject of our first investigation of whether we should consider adding different variables. Table 2.12 is a full model which includes all of the original variables as well as the squared value of all of the original values. These variables account for the fact that if avginc is significantly higher in certain states, that could significantly reduce the number of violent crimes in that state. Another example would be that if the pm1029 is significantly higher in certain areas, then that could have exponential effects on violent crimes. So, these relationships were investigated with an f-test that compared the full model in Table 2.12 to the reduced model in Table 2.2. Per Table 2.12, it is evident that some of these variables are in fact very strong indicators of violent crime rate. So, unsurprisingly, the f-test, which can be seen in Table 2.13, provides very significant evidence that there are some quadratic relationships in the data which should be accounted for. Again, these variables will be considered in the final model evaluation algorithm.

Next, interaction variables were considered. In Table 2.14, each variable was interacted with others so that every bi-variate interaction was considered. Stateid specific interactions as well as yearly specific interactions were not considered for the simple purpose of reducing the number of variables that must be worked with in the model, and to reduce the risk of over-fitting, most importantly. Overfitting is a common problem in many regressions which will only serve to reduce the predictive value of the model, and may obscure the effects of shall laws on violent crimes. Anyways, it seems from the initial regression that many of those interactions are significant. Most of them seem to comply with basic econometric theory like the interaction between robbery and population density which is significant at a 1% level, and is likely to increase violent crime by 1.5 instances per 100,000. The follow-up f-test which compared Table 2.2 to table 2.14 can be seen in Table 2.15. This f-test in Table 2.15 yielded an f-statistic of 19, which is very strong evidence that interaction variables do have explanatory value, and should be considered. However, not all of these variables are necessary of value, and so that takes us to our next phase in our analysis.

Final Model Specification:

The final phase in model specification analysis includes the utilization of an algorithm to test variables for their contributory value in explaining violent crime rates. Specifically, this algorithm aims to minimize AIC and BIC while maximizing the adjusted r-squared value. This algorithm will add and subtract variables until no more can be added or subtracted that reduce AIC and BIC or increase the adjusted r-squared. Therefore, this algorithm can effectively eliminate all useless variables while leaving the most significant ones and ultimately delivering the model that best fits the data and most effectively explains the dependent variable. This algorithm is an efficient way to cut through some of the clutter and find truly valuable explanatory variables, thereby allowing us better insight into t7he true effects from shall-issue laws. This algorithm effectively combines all of the best quadratic, interaction, fixed effects and original variables into a single, digestible model. Multiple iterations and versions of this final model were created, and the theory behind each iteration will be discussed. Then, the final model will be analyzed in further detail. Importantly, the manner in which the reduced and full models are fed into the algorithm can impact the results. Also, the method of either forward variable addition/subtraction, backward, or both can significantly impact the results and the relative value of shall laws' explanatory value.

Since there are material effects on the variable of interest depending on the nature of the algorithm that is used, there are some important tweaks made before deciding on a final model. As you will see, this process must be understood well when using this algorithm, or it can actually obscure the true impact on the variable of interest on the dependent variable by overfitting the model, adding too many variables we are uninterested in, or in omitting variables we are interested in.

The first iteration in using this algorithm to understand this data used a reduced model that only included an intercept. There were no other variables than the intercept included in this reduced model because our group thought it would be interesting to see if the algorithm selected the shall variable, or functions of the shall variable, as variables in this model. The reduced model used in this step can be seen in Table 2.15, while the full model including every single fixed effect, quadratic, and interaction variable can be seen in Table 2.16. An f-test was performed, per Table 2.17, to compare the two models, and results were unsurprisingly conclusive of the fact that at least one of the variables in the full model have significant explanatory value. A f-stat of 579 affirms this fact. Next, the algorithm was performed which began with the intercept, and added variables from the 'variable pool' of the full model. This final model contained only the variables which improved the overall value of the model in regards to minimizing AIC, BIC and maximizing the adjusted r-squared. The results of this initial algorithm can be seen in Table 2.18.

The regression in Table in 2.18 indicates interesting insight into the impact from shall laws on reducing violent crimes. Whether shall laws exist by themselves is not a significant variable in this model as it does not exist. It was not added by the algorithm suggesting it does not improve the value of the model, and that all of the other variables in the full model provide more significant value in predicting the violent crime rate. If we stopped here, we would assume that shall laws do not, by themselves, reduce violent crimes. Although four interaction variables including shall were included as relevant in this model, shall was not by itself. These four interaction variables imply interesting relationships between where shall laws are issued and correlating characteristics of the state which issued those laws, and may not imply causal relationships by themselves.

The econometric theory is compelling in some of these cases, and results are surprising. First, it seems as though the percentage of the population from 10-64 that's white has an interaction with shall laws, and this may be because white people are more or less affluent in some way, or violent crimes are charged differently for white people where shall laws exist. Accordingly, as the pw1064 increases where there are shall laws, there tends to be a slightly lower violent crime rate. Also, interestingly, wherever there are shall laws, and there are high robberies, violent crimes actually increase. Although this makes sense with the robbery variable being so correlated with violent crimes, it is its interaction with the shall issue law that makes it so interesting. First, this variable entails that this interaction causes violent crimes to increase. Why would more robberies be violent crimes in states where there are shall-issue laws?

Well, maybe some conservatives are correct when they say that legal weapons can deter criminals from trying to rob by force. If there are no shall-issue laws, it may make more criminals more scared about trying to rob someone at gunpoint. Alternatively, if criminals know that most people are armed, they will probably not try to violently rob someone. The exact same thesis is true regarding the interaction variable between shall and pm1029. As males 29 and younger perform most violent crimes, those individuals may be more likely to perform such an act if they assume their victim is unarmed.

However, although that thesis may hold regarding robberies and young males, it may not be the case with murders. The third interaction variable involving shall laws entails that as murders increase where there are shall laws, violent crime decreases. This may entail that as murders occur, shall laws allow more empowerment to law enforcement for finding those violent criminals and preventing them from violently harming others as shall laws usually require that all weapons be licensed, registered, and on file with a government entity, thereby making forensic evidence more rich and meaningful (i.e. type of bullet wound). These results make sense when you think about it, but are somewhat surprising. Unfortunately, however, this model is not truly a fixed effects model as it only adds in the fixed effects variables which tend to have the most explanatory value. A true fixed effects model ought to have all the necessary dummy variables for each entity and for each year, in this case. So, bearing this in mind, our group decided to create a different model where the base model included all of the fixed effects variables so that we do not accidentally materially interfere with the true effects from shall laws. Another reason to create another iteration was because we thought it necessary to include the shall variable in the model to test for its effectiveness, and to use it as a reference point regardless of whether the algorithm decided to include that variable or not.

The second iteration of the final model specification began with more than just the intercept. Actually, the reduced model fed into the second iteration of this algorithm included all of the original variables in the dataset as well as all of the state-specific and yearly fixed effects variables. This was done for two important reasons: Firstly, it will not omit the actual variable of interest. Omitting the primary variable of interest in this study (shall laws) makes no sense. Second, it will now be a true fixed effects model which attributes fixed effects variables for every necessary entity and year as opposed to only adding fixed effects where they added explanatory value to the model. Now, we can claim that this model is a true fixed effects model which accounts for the effects of omitted within entity fixed effects, as well as the effects for yearly fixed effects consistent across all entities. The base model for this second iterative step can be found in Table 2.11 while the full model can be found in Table 2.16, similar to above.

The divergence from the first iteration comes in at adjusting the reduced model to reflect our variable of interest by not allowing the algorithm to reject that variable from the model. Then, the same algorithm was performed using both forward and backward variable addition. The results of this second iteration can be found in Table 2.20 and the significant variables involving shall-issue laws are further summarized in Table 2.21. Now, shall is highly significant as a standalone variable! It reduces violent crimes by 2.27 cases per 100,000. This is significant results which appropriately account for omitted variables that are fixed within-entity, and by year. This model in Table 2.20 also accounts for non-linear and quadratic variables in a meaningful way, thereby making the results for shall laws highly significant. These are fascinating, exciting results! Shall-issue's interaction with robbery, murder, pm1029 were also included in this model, and the interpretations for them are nearly the same. However, a couple more variables were added, while one was removed. The variable that was removed from the first iteration but that was removed from the second iteration is the interaction with the pw1064*shall. This is interesting. Further, the variables that were included in the second iteration but that were not included in the first iteration, other than shall itself, is shall's interaction with incarc_rate and shall's interaction with density. To interpret these results, you cannot assume a causal relationship as it may simply be a correlatory one.

However, it is possible that as the population density increases in certain areas, the propensity for there to be more crime and for there to be the existence of gun laws increases. The interaction variable density*shall is a perfect example of correlation versus causation. Both of these variables are likely to come hand-in-hand and may simply be because more populous states tend to be more progressive states, so this would not be a causal relationship. However, for the other interaction variable, incarc_rate*shall, it seems to follow the same principle or thesis as the mur and rob variables. Criminals are more likely to be encouraged to violently assault their victims if there are more restrictions on legal gun ownership for those who adhere to the law.

<u>Interpretation of Results:</u>

Table 2.2 - Reference Model with all the original explanatory variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 4000% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 decreases violent crime rate by about 520%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 890%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 157%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 598%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population decreases violent crime rate by 21%, which makes “pop” variable significant.

Table 2.5 - reduced model excluding correlated variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 7825% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 decreases violent crime rate by about 2413%, which makes “pm1029” variable significant.

- When everything else held constant,1% increase in population per square mile of land area increases violent crime rate by 13200%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population increases violent crime rate by 2025%, which makes “pop” variable significant.

Table 2.7 - full model with stateid fixed effects variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 2324% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 decreases violent crime rate by about 1845%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 960%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 140%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 440%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population increases violent crime rate by 1300%, which makes “pop” variable significant.

Table 2.9 - yearly fixed effects variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 4580% compared to states that did not have shall-issue laws, which makes “shall” variable significant.

- When everything else held constant, an increase of 1 % in percent of state population that is male ages 10 to 29 increases violent crime rate by about 1841%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 795%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 160%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 558%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population decreases violent crime rate by 22%, which makes “pop” variable significant.

Table 2.11 - both year and stateid FE variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 1900% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 increases violent crime rate by about 2150%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 750%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 130%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 1170%, which makes the “density” variable significant.

- When everything else held constant,1% increase in state population increases violent crime rate by 70%, which makes “pop” variable significant.

Table 2.12 - quadratic variable model

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 1900% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 increases violent crime rate by about 2150%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 750%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 130%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 1170%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population increases violent crime rate by 70%, which makes “pop” variable significant.

Table 2.14 - full interaction variable model

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 2700% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 decreases violent crime rate by about 10700%, which makes “pm1029” variable significant.

- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 1280%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) increase violent crime rate by about 1720%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area increases violent crime rate by 600%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population decreases violent crime rate by 1300%, which makes “pop” variable significant.

Table 2.16 - Full model including all variables

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 9300% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant, increase of 1 % in percent of state population that is male ages 10 to 29 decreases violent crime rate by about 16000%, which makes “pm1029” variable significant.
- When everything else held constant,1% increase in murder rate (incidents per 100,000) increase violent crime rate by about 6400%, which makes “mur” variable significant.
- When everything else held constant,1% increase in robbery rate (incidents per 100,000) decrease violent crime rate by about 512%, which makes “rob” variable significant.
- When everything else held constant,1% increase in population per square mile of land area decreases violent crime rate by 35000%, which makes the “density” variable significant.
- When everything else held constant,1% increase in state population decreases violent crime rate by 11000%, which makes “pop” variable significant.

Table 2.19 - summary of shall-issue related results for first iteration of final model

- When everything else held constant, increase of 1 % in percent of the interaction of state population that is male ages 10 to 64 and states with shall-issues laws decreases violent crime rate by about 140%, which makes “pm1064” variable significant.
- When everything else held constant,1% increase in interaction of robbery rate (incidents per 100,000) and shall-issue laws increase violent crime rate by about 380%, which makes “rob” variable significant.
- When everything else held constant,1% increase in interaction of murder rate (incidents per 100,000) and shall-issue laws decreases violent crime rate by about 490%, which makes “mur” variable significant.
- When everything else held constant, increase of 1 % in percent of the interaction of state population that is male ages 10 to 29 and states with shall-issues laws increases violent crime rate by about 390%, which makes “pm1029” variable significant.

Table 2.21 - significant variables involving shall from regression in Table 2.20

- When everything else held constant, states with shall-issue laws had a violent crime rate decrease by approximately by about 223% compared to states that did not have shall-issue laws, which makes “shall” variable significant.
- When everything else held constant,1% increase in interaction of robbery rate (incidents per 100,000) and shall-issue laws increase violent crime rate by about 270%, which makes “rob” variable significant.
- When everything else held constant,1% increase in interaction of murder rate (incidents per 100,000) and shall-issue laws decreases violent crime rate by about 450%, which makes “mur” variable significant.
- When everything else held constant, increase of 1 % in percent of the interaction of state population that is male ages 10 to 29 and states with shall-issues laws increases violent crime rate by about 990%, which makes “pm1029” variable significant.

- When everything else held constant,1% increase in interaction of incarceration rate in the state in the previous year and shall-issue laws increases violent crime by about 115%, which makes “incarc_rate” variable significant.
- When everything else held constant,1% increase in interaction of population per square mile of land area and shall-issue laws increases violent crime rate by about 193%, which makes “density” significant.

Conclusion:

Given the observational nature of paper, we have been successful in analyzing the impact of these laws. We can clearly understand the Qualitative relationship between variables based on interpretation results discussed above. As discussed previously, we have gone ahead with a Fixed Effects Model that allows for more precision in this case. The process has been pretty straightforward. We initiated with a base model and have tried to incorporate multiple models and noted their findings which have then been used in our final analysis. Here, a logline has been used to describe the effects of multiple models on the final analysis while highlighting their key outputs. Model 1 used shall Dummy Variable as the standalone dummy variable and the results highlighted the importance of Shall while flaunting its high level of significance. Model 2 was a non Fixed Effects Model which highlighted explanatory variables and the results concluded their high level of significance into the understanding of the model. Model 3 tries to establish explanatory nature of correlated variables and the results show that these variables are to be accounted for in the final model.

The forthcoming models introduce Fixed effects models while introducing dummy variables, performing relevant tests and checking for their level of significance in the overall scheme of things while not violating the economic theory. Model 4 includes all of the stateid dummy variables which account for omitted variables with constant effects within each individual state entity that may impact the results of the analysis.This model concludes that there are in fact constant effects within each state that are omitted which are relevant predictors of violent crime rates. Model 5 discusses the results of the yearly fixed effects model and the reduced model it is being compared with. The f-test which is significant at a 1% alpha level indicates that there are in fact some yearly fixed effects which affect all state entities the same, but that vary each year and will also be considered in the final model.

Model 6 contains both the yearly fixed effects and the stateid fixed effects variables to determine if the shall variable was still a valid predictor of the violent crime rate. As Per the results, shall is still a valid predictor of violent crime rates even at a 1% significance level. This is very strong evidence that shall-issue laws do help reduce the crime rate**.** Model 7 helped in analysing and introducing Quadratic relationships within the Model after a series of successful F-Tests.Model 8 discusses and establishes interaction variables within the model. It is to be duly noted that a large number of those were insignificant and only the most relevant ones have been added.All of these models have tried to touch upon certain aspects of relevance. After determining to use the fixed effects model controlling for both within entity and yearly constant omitted effects, we utilized a machine learning algorithm to aim to determine which variables needed to be included in the final model.

Then, we were able to ascertain the most accurate perspective possible into the implications of shall-issue laws regulating the ownership of guns. We have been bent on incorporating factors from our analysis that seem to have affected the final model. Based on that, we have come across some observations. In our Final Model, as we can see in Table 2.20, we have been able to list out the qualitative nature of all the significant variables.We have proceeded to establish digestible relationships amongst all the different types of variables. We have tried to interpret the results between these variables and establish a quantifiable relationship with our goal. We have tried to show in a linear tabularly manner, how the tests were performed, how the outcomes were reached and how certain characteristics and insights were taken from each model to build our final model.

The Table 2.20 is our Final model which indicates all the significant variables. Upon completing all of the analysis regarding which variables to include in the final model, we found that shall laws do in fact indicate they may help to reduce violent crimes. The final model included the aggregate of all the significant variables discovered over a series of iterations of regression models and corresponding f-tests. Specifically, this final model included entity-specific stateid variables, yearly fixed effects variables, quadratic variables, interaction variables, and the original variables in the Gun dataset.All these variables have been tested previously for Significance and only the most significant variables have been considered. Our model has been evolved after continuous analysis of the dataset and proposing theories and rejecting most while encountering and considering the findings from each of those which serve as the foundation for our Model.

Model Specification Tables (Section 2):

Table 2.1 - Reduced model with shall as standalone explanatory variable

```
> summary(original.red.reg)

Call:
lm(formula = gun.original$vio ~ gun.original$shall, data = gun.original)

Residuals:
    Min      1Q  Median      3Q     Max 
-495.24 -228.84  -63.64  134.06 2379.56 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)          542.24      10.98  49.386  < 2e-16 ***
gun.original$shall  -161.19      22.27  -7.236 8.32e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 327.2 on 1171 degrees of freedom
Multiple R-squared:  0.0428,	Adjusted R-squared:  0.04199 
F-statistic: 52.36 on 1 and 1171 DF,  p-value: 8.319e-13
```

Table 2.2 - Reference Model with all the original explanatory variables

```
> summary(original.reg)

Call:
lm(formula = gun.original$vio ~ ., data = gun.original)

Residuals:
    Min      1Q  Median      3Q     Max 
-370.42  -69.53  -12.35   49.60  435.44 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 168.14955  133.14093   1.263   0.2069    
mur           8.90464    0.98788   9.014  < 2e-16 ***
rob           1.57001    0.04387  35.784  < 2e-16 ***
incarc_rate   0.46553    0.03439  13.537  < 2e-16 ***
pb1064       -0.34980    4.08299  -0.086   0.9317    
pw1064        0.63471    2.05029   0.310   0.7569    
pm1029       -5.18771    2.79586  -1.855   0.0638 .  
pop          -0.21409    0.75880  -0.282   0.7779    
avginc       -1.14566    1.94879  -0.588   0.5567    
density     -59.78928    4.63542 -12.898  < 2e-16 ***
shall       -40.03537    8.04902  -4.974 7.55e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 104.6 on 1162 degrees of freedom
Multiple R-squared:  0.903,	Adjusted R-squared:  0.9021 
F-statistic:  1081 on 10 and 1162 DF,  p-value: < 2.2e-16
```

Table 2.3 - ANOVA-based f-test comparing Table 2.1 and Table 2.2 regressions

```
> anova(original.reg, original.red.reg)
Analysis of Variance Table

Model 1: gun.original$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall
Model 2: gun.original$vio ~ gun.original$shall
  Res.Df       RSS Df  Sum of Sq      F    Pr(>F)
1   1162  12708545
2   1171 125355176 -9 -112646631 1144.4 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

Table 2.4 - correlation heatmap

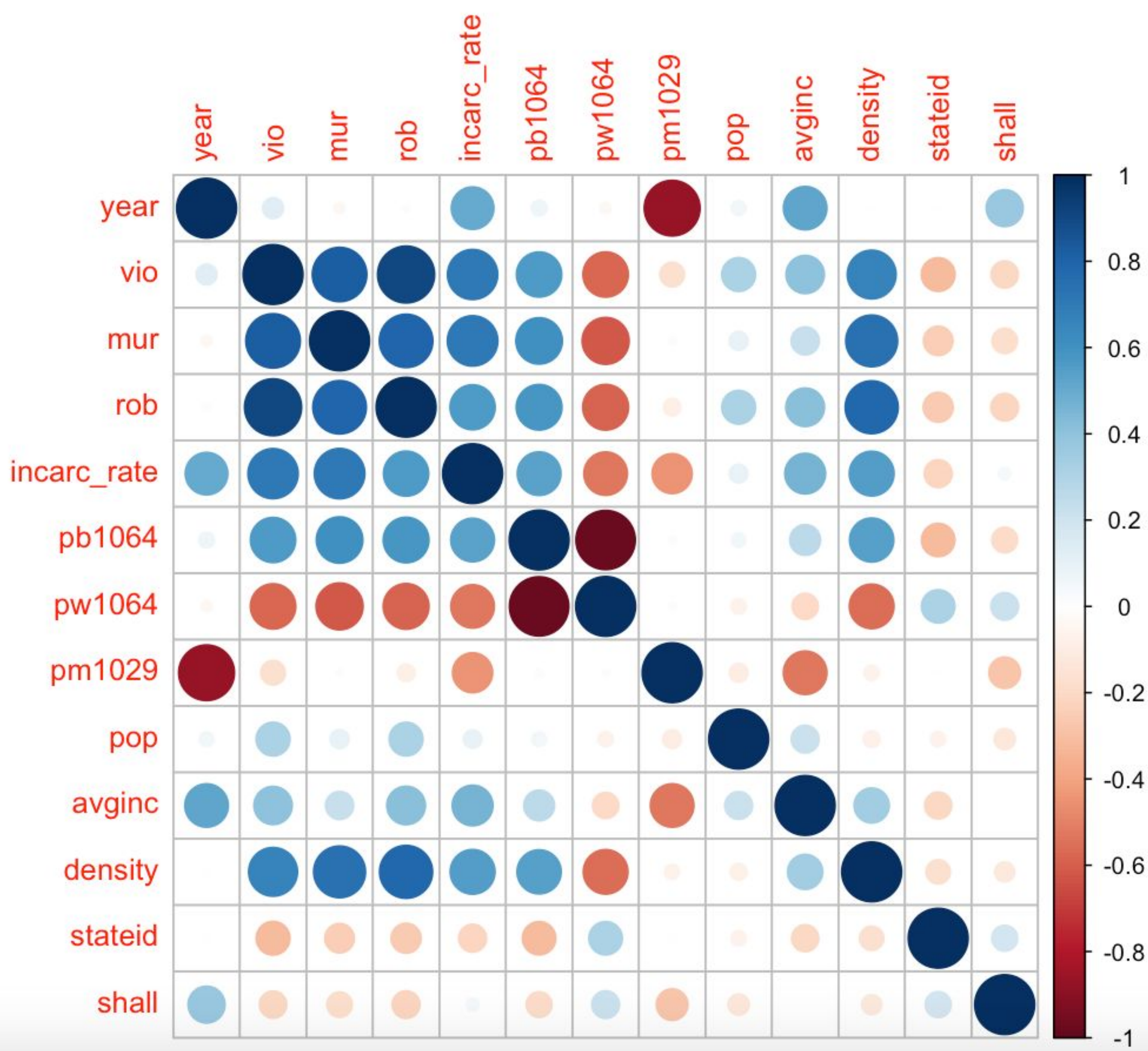


Table 2.5 - reduced model excluding correlated variables

```
> summary(red.cor)

Call:
lm(formula = gun.original$vio ~ gun.original$pb1064 + gun.original$pw1064 +
    gun.original$pm1029 + gun.original$pop + gun.original$avginc +
    gun.original$density + gun.original$shall, data = gun.original)

Residuals:
    Min      1Q  Median      3Q     Max
-717.93 -134.83  -23.49  126.18  934.02

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           435.297    251.778   1.729  0.08409 .
gun.original$pb1064    21.786      7.775   2.802  0.00516 **
gun.original$pw1064     2.787      3.925   0.710  0.47787
gun.original$pm1029   -24.126      4.609  -5.234 1.96e-07 ***
gun.original$pop       20.251      1.194  16.959  < 2e-16 ***
gun.original$avginc     2.850      3.644   0.782  0.43437
gun.original$density  131.937      5.727  23.036  < 2e-16 ***
gun.original$shall    -78.250     15.233  -5.137 3.27e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 200.4 on 1165 degrees of freedom
Multiple R-squared:  0.6428,	Adjusted R-squared:  0.6406
F-statistic: 299.5 on 7 and 1165 DF,  p-value: < 2.2e-16
```

Table 2.6 - F-test comparing Table 2.2 with Table 2.5

```
> anova(full.cor, red.cor)
Analysis of Variance Table

Model 1: gun.original$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall
Model 2: gun.original$vio ~ gun.original$pb1064 + gun.original$pw1064 +
    gun.original$pm1029 + gun.original$pop + gun.original$avginc +
    gun.original$density + gun.original$shall
  Res.Df      RSS Df Sum of Sq      F    Pr(>F)
1   1162 12708545
2   1165 46781352 -3 -34072807 1038.5 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Table 2.7 - full model with stateid fixed effects variables

```
Call:
lm(formula = gun.state.dummy$vio ~ ., data = gun.state.dummy)

Residuals:
     Min       1Q   Median       3Q      Max 
-246.188  -33.682   -0.566   28.188  269.577 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  288.64145  130.69942   2.208 0.027417 *  
mur            9.56615    0.68261  14.014  < 2e-16 ***
rob            1.38324    0.03831  36.108  < 2e-16 ***
incarc_rate    0.21669    0.03263   6.641 4.86e-11 ***
pb1064        -2.61661    6.20746  -0.422 0.673452    
pw1064         3.24201    1.71191   1.894 0.058511 .  
pm1029       -18.44771    2.22439  -8.293 3.15e-16 ***
pop           12.77254    2.94497   4.337 1.57e-05 ***
avginc         0.68237    2.06065   0.331 0.740600    
density       -4.44255   28.68611  -0.155 0.876954    
shall        -23.23604    6.33425  -3.668 0.000256 ***
stateid_2    157.52182   24.95556   6.312 3.97e-10 ***
stateid_4      3.93978   31.38321   0.126 0.900120    
stateid_5    -46.99355   22.69972  -2.070 0.038662 *  
stateid_6   -266.02103   77.19004  -3.446 0.000590 ***
stateid_8    -39.47013   39.52516  -0.999 0.318202    
stateid_9   -192.98879   47.16988  -4.091 4.60e-05 ***
stateid_10    48.33453   27.51048   1.757 0.079202 .  
stateid_11  -111.35387  270.32037  -0.412 0.680468    
stateid_12    45.84539   38.94658   1.177 0.239393    
stateid_13   -74.17347   18.10817  -4.096 4.51e-05 ***
stateid_15    -0.70685   88.24443  -0.008 0.993610    
stateid_16   -65.39504   43.13867  -1.516 0.129822    
stateid_17   -95.60965   37.00180  -2.584 0.009895 ** 
stateid_18  -125.43644   38.02977  -3.298 0.001003 ** 
stateid_19  -129.82224   45.14407  -2.876 0.004108 ** 
stateid_20   -82.57100   36.01668  -2.293 0.022058 *  
stateid_21  -152.82800   36.08654  -4.235 2.47e-05 ***
stateid_22    75.26256   19.56993   3.846 0.000127 ***
stateid_23  -168.11561   46.58908  -3.608 0.000322 ***
stateid_24   -10.75817   21.58301  -0.498 0.618261    
stateid_25    13.46549   51.35458   0.262 0.793211    
stateid_26   -93.07260   34.01264  -2.736 0.006310 ** 
stateid_27  -179.99205   44.12412  -4.079 4.84e-05 ***
stateid_28   -80.91995   26.45818  -3.058 0.002278 ** 
stateid_29   -91.89610   32.13602  -2.860 0.004321 ** 
stateid_30  -151.24693   36.99183  -4.089 4.65e-05 ***
stateid_31   -85.98771   40.67701  -2.114 0.034745 *  
stateid_32  -113.22070   32.39117  -3.495 0.000492 ***
stateid_33  -186.85873   49.10178  -3.806 0.000149 ***
stateid_34  -199.13891   43.35179  -4.594 4.85e-06 ***
stateid_35   220.01882   26.48632   8.307 2.83e-16 ***
stateid_36  -325.50662   50.57152  -6.437 1.81e-10 ***
stateid_37   -29.12856   18.35234  -1.587 0.112755    
stateid_38  -166.52724   39.72052  -4.192 2.98e-05 ***
stateid_39  -256.92911   42.77778  -6.006 2.57e-09 ***
stateid_40   -34.97726   23.90359  -1.463 0.143678    
stateid_41   -56.98378   40.96641  -1.391 0.164507    
stateid_42  -298.41201   46.27956  -6.448 1.69e-10 ***
stateid_44   -70.54124   53.98030  -1.307 0.191552    
stateid_45   269.70957   19.29637  13.977  < 2e-16 ***
stateid_46  -119.65485   35.39218  -3.381 0.000748 ***
stateid_47   -62.15930   24.62983  -2.524 0.011750 *  
stateid_48  -245.48089   48.58149  -5.053 5.08e-07 ***
stateid_49   -46.20506   40.62393  -1.137 0.255622    
stateid_50  -162.36633   47.45608  -3.421 0.000646 ***
stateid_51  -208.31615   20.71059 -10.058  < 2e-16 ***
stateid_53   -61.65481   36.17299  -1.704 0.088578 .  
stateid_54  -194.86404   42.11035  -4.627 4.14e-06 ***
stateid_55  -234.29207   41.09778  -5.701 1.53e-08 ***
stateid_56   -51.74356   43.20970  -1.197 0.231367    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 53.67 on 1112 degrees of freedom
Multiple R-squared:  0.9755,	Adjusted R-squared:  0.9742 
F-statistic: 739.1 on 60 and 1112 DF,  p-value: < 2.2e-16
```

Table 2.8 - f-test comparing FE model in Table 2.7 to Table 2.2

```
> anova(full.st.reg, red.st.reg)
Analysis of Variance Table

Model 1: gun.state.dummy$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall + stateid_2 + stateid_4 +
    stateid_5 + stateid_6 + stateid_8 + stateid_9 + stateid_10 +
    stateid_11 + stateid_12 + stateid_13 + stateid_15 + stateid_16 +
    stateid_17 + stateid_18 + stateid_19 + stateid_20 + stateid_21 +
    stateid_22 + stateid_23 + stateid_24 + stateid_25 + stateid_26 +
    stateid_27 + stateid_28 + stateid_29 + stateid_30 + stateid_31 +
    stateid_32 + stateid_33 + stateid_34 + stateid_35 + stateid_36 +
    stateid_37 + stateid_38 + stateid_39 + stateid_40 + stateid_41 +
    stateid_42 + stateid_44 + stateid_45 + stateid_46 + stateid_47 +
    stateid_48 + stateid_49 + stateid_50 + stateid_51 + stateid_53 +
    stateid_54 + stateid_55 + stateid_56
Model 2: gun.state.dummy$vio ~ gun.state.dummy$mur + gun.state.dummy$rob +
    gun.state.dummy$incarc_rate + gun.state.dummy$pb1064 + gun.state.dummy$pw1064 +
    gun.state.dummy$pm1029 + gun.state.dummy$pop + gun.state.dummy$avginc +
    gun.state.dummy$density + gun.state.dummy$shall
  Res.Df      RSS  Df Sum of Sq      F    Pr(>F)
1   1112  3203534
2   1162 12708545 -50  -9505011 65.987 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
```

Table 2.9 - yearly fixed effects variables

```
> summary(full.yr.reg)

Call:
lm(formula = gun.year.dummy$vio ~ ., data = gun.year.dummy)

Residuals:
    Min      1Q  Median      3Q     Max 
-324.52  -63.67  -11.30   42.51  387.65 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -45.59118  141.79536  -0.322 0.747869    
mur           7.95308    0.99791   7.970 3.83e-15 ***
rob           1.61867    0.04520  35.809  < 2e-16 ***
incarc_rate   0.45246    0.03782  11.965  < 2e-16 ***
pb1064       -7.93414    4.49571  -1.765 0.077861 .  
pw1064       -2.58346    2.24010  -1.153 0.249037    
pm1029       18.41295    4.43055   4.156 3.48e-05 ***
pop          -0.22127    0.74970  -0.295 0.767942    
avginc       -1.21698    2.00378  -0.607 0.543746    
density     -55.82783    4.58639 -12.172  < 2e-16 ***
shall       -45.80444    8.24779  -5.554 3.48e-08 ***
year_78      12.30541   20.28137   0.607 0.544148    
year_79      24.18010   20.31154   1.190 0.234113    
year_80      15.58810   20.40069   0.764 0.444968    
year_81       9.52933   20.49157   0.465 0.641994    
year_82      20.61066   20.63321   0.999 0.318052    
year_83      25.17678   20.90279   1.204 0.228658    
year_84      49.66647   21.27890   2.334 0.019765 *  
year_85      63.10355   21.70538   2.907 0.003716 ** 
year_86      77.05665   22.20690   3.470 0.000540 ***
year_87      83.33339   22.85684   3.646 0.000278 ***
year_88      95.38922   23.48389   4.062 5.20e-05 ***
year_89      97.09530   24.09064   4.030 5.94e-05 ***
year_90     127.94127   25.16677   5.084 4.32e-07 ***
year_91     128.78864   25.82325   4.987 7.07e-07 ***
year_92     148.23202   26.48227   5.597 2.72e-08 ***
year_93     151.96290   27.02292   5.623 2.35e-08 ***
year_94     142.90628   27.69084   5.161 2.90e-07 ***
year_95     132.82700   28.40715   4.676 3.28e-06 ***
year_96     117.09173   29.10669   4.023 6.13e-05 ***
year_97     122.77994   29.77489   4.124 4.00e-05 ***
year_98     113.65710   30.45519   3.732 0.000199 ***
year_99      95.93485   31.11121   3.084 0.002094 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 102.3 on 1140 degrees of freedom
Multiple R-squared:  0.9089,	Adjusted R-squared:  0.9064 
F-statistic: 355.5 on 32 and 1140 DF,  p-value: < 2.2e-16
```

Table 2.10 - f-test comparing yearly FE model in 2.9 with Table 2.2

```
> anova(full.yr.reg, red.yr.reg)
Analysis of Variance Table

Model 1: gun.year.dummy$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall + year_78 + year_79 +
    year_80 + year_81 + year_82 + year_83 + year_84 + year_85 +
    year_86 + year_87 + year_88 + year_89 + year_90 + year_91 +
    year_92 + year_93 + year_94 + year_95 + year_96 + year_97 +
    year_98 + year_99
Model 2: gun.year.dummy$vio ~ gun.year.dummy$mur + gun.year.dummy$rob +
    gun.year.dummy$incarc_rate + gun.year.dummy$pb1064 + gun.year.dummy$pw1064 +
    gun.year.dummy$pm1029 + gun.year.dummy$pop + gun.year.dummy$avginc +
    gun.year.dummy$density + gun.year.dummy$shall
  Res.Df      RSS  Df Sum of Sq      F   Pr(>F)
1   1140 11927707
2   1162 12708545 -22   -780839 3.3922 2.28e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 2.11 - both year and stateid FE variables

```
> summary(gun.yr.st.dummy.reg)

Call:
lm(formula = gun.yr.st.dummy$vio ~ ., data = gun.yr.st.du

Residuals:
     Min       1Q   Median       3Q      Max
-185.644  -28.941   -1.771   25.072  275.394

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  257.80725  167.39162   1.540 0.123815
mur            7.51748    0.65695  11.443  < 2e-16 ***
rob            1.30343    0.03643  35.774  < 2e-16 ***
incarc_rate    0.26337    0.03331   7.907 6.43e-15 ***
pb1064       -24.92207    8.18953  -3.043 0.002397 **
pw1064        -5.89360    2.78986  -2.113 0.034870 *
pm1029        21.54559    5.58226   3.860 0.000120 ***
pop            7.02944    2.81653   2.496 0.012715 *
avginc         2.43892    2.37796   1.026 0.305290
density      -11.70161   27.16357  -0.431 0.666711
shall        -19.01252    6.09543  -3.119 0.001861 **
stateid_2     86.74404   25.06776   3.460 0.000560 ***
stateid_4    -31.88044   29.81089  -1.069 0.285116
stateid_5    -64.62943   22.26722  -2.902 0.003777 **
stateid_6   -135.75505   74.10057  -1.832 0.067219 .
stateid_8    -59.66682   37.09915  -1.608 0.108058
stateid_9   -177.36250   46.02116  -3.854 0.000123 ***
stateid_10    27.68514   26.64564   1.039 0.299030
stateid_11   129.57365  264.59353   0.490 0.624439
stateid_12   134.71507   37.55908   3.587 0.000350 ***
stateid_13   -61.31192   17.97850  -3.410 0.000673 ***
stateid_15    30.79211   85.41933   0.360 0.718557
stateid_16  -151.60689   43.19545  -3.510 0.000467 ***
stateid_17   -41.35096   35.22203  -1.174 0.240648
stateid_18  -139.87423   35.59169  -3.930 9.03e-05 ***
stateid_19  -177.91039   43.60667  -4.080 4.83e-05 ***
stateid_20  -128.97168   34.72360  -3.714 0.000214 ***
stateid_21  -179.14584   34.19962  -5.238 1.94e-07 ***
stateid_22    62.67033   18.17431   3.448 0.000586 ***
stateid_23  -200.73257   44.19031  -4.542 6.18e-06 ***
stateid_24    47.57883   26.37642   1.804 0.071532 .
stateid_25    23.35996   48.69620   0.480 0.631531
stateid_26   -65.66209   32.03049  -2.050 0.040605 *
stateid_27  -210.38376   41.80621  -5.032 5.66e-07 ***
stateid_28  -120.19354   25.32223  -4.747 2.34e-06 ***
stateid_29   -84.10942   30.05520  -2.798 0.005225 **
stateid_30  -190.73568   35.48174  -5.376 9.33e-08 ***
stateid_31  -140.67443   39.76546  -3.538 0.000421 ***
stateid_32   -96.60257   31.16910  -3.099 0.001989 **
stateid_33  -220.97019   46.35690  -4.767 2.13e-06 ***
stateid_33  -220.97019   46.35690  -4.767 2.13e-06 ***
stateid_34  -131.26031   44.51856  -2.948 0.003262 **
stateid_35   182.42489   26.28384   6.941 6.69e-12 ***
stateid_36  -189.16218   50.94752  -3.713 0.000215 ***
stateid_37   -21.71788   17.57340  -1.236 0.216785
stateid_38  -273.38291   41.47176  -6.592 6.75e-11 ***
stateid_39  -219.97596   40.18958  -5.473 5.47e-08 ***
stateid_40   -60.25543   22.43615  -2.686 0.007349 **
stateid_41   -59.08753   38.37273  -1.540 0.123892
stateid_42  -236.31250   43.76446  -5.400 8.19e-08 ***
stateid_44   -99.08833   50.83437  -1.949 0.051523 .
stateid_45   249.26865   18.14421  13.738  < 2e-16 ***
stateid_46  -203.14131   36.12586  -5.623 2.38e-08 ***
stateid_47   -43.34749   22.91421  -1.892 0.058792 .
stateid_48  -208.36860   45.32303  -4.597 4.78e-06 ***
stateid_49  -204.62507   46.30619  -4.419 1.09e-05 ***
stateid_50  -215.01088   45.10525  -4.767 2.12e-06 ***
stateid_51  -198.05412   21.46038  -9.229  < 2e-16 ***
stateid_53   -68.12636   34.09075  -1.998 0.045923 *
stateid_54  -208.07275   40.02843  -5.198 2.40e-07 ***
stateid_55  -266.55170   38.95237  -6.843 1.29e-11 ***
stateid_56  -133.17752   41.87739  -3.180 0.001513 **
year_78       13.83952    9.95896   1.390 0.164917
year_79       33.71978   10.15288   3.321 0.000926 ***
year_80       35.93008   10.42255   3.447 0.000588 ***
year_81       33.26834   10.83421   3.071 0.002189 **
year_82       41.77316   11.32477   3.689 0.000237 ***
year_83       42.51595   12.06571   3.524 0.000443 ***
year_84       62.83628   13.30389   4.723 2.62e-06 ***
year_85       77.15307   14.54541   5.304 1.37e-07 ***
year_86       93.96105   15.97446   5.882 5.39e-09 ***
year_87       98.75222   17.41291   5.671 1.82e-08 ***
year_88      114.95964   19.06367   6.030 2.24e-09 ***
year_89      122.08890   20.60749   5.924 4.20e-09 ***
year_90      166.98497   25.27832   6.606 6.17e-11 ***
year_91      174.52186   26.55778   6.571 7.71e-11 ***
year_92      194.19895   28.01673   6.932 7.11e-12 ***
year_93      200.62944   29.10619   6.893 9.23e-12 ***
year_94      192.38309   30.42047   6.324 3.71e-10 ***
year_95      183.99488   31.70936   5.803 8.55e-09 ***
year_96      164.91235   32.88723   5.014 6.20e-07 ***
year_97      166.49572   34.03154   4.892 1.15e-06 ***
year_98      154.45458   35.38553   4.365 1.39e-05 ***
year_99      136.57306   36.63950   3.727 0.000203 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 49.54 on 1090 degrees of freedom
Multiple R-squared:  0.9796,    Adjusted R-squared:  0.978
F-statistic: 637.5 on 82 and 1090 DF,  p-value: < 2.2e-16
```

Table 2.12 - quadratic variable model

```
> summary(nonlin.reg.full)

Call:
lm(formula = gun.original$vio ~ . + I(gun.original$incarc_rate^2) +
    I(gun.original$density^2) + I(gun.original$rob^2) + I(gun.original$mur^2) +
    I(gun.original$avginc^2) + I(gun.original$pb1064^2) + I(gun.original$pw1064^2) +
    I(gun.original$pop^2) + I(gun.original$pm1029^2), data = gun.original)

Residuals:
    Min      1Q  Median      3Q     Max
-268.49  -55.91  -11.07   46.45  401.00

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                  -1.703e+01  5.052e+02  -0.034 0.973111
mur                           1.276e+01  1.947e+00   6.553 8.46e-11 ***
rob                           1.721e+00  7.374e-02  23.343  < 2e-16 ***
incarc_rate                   4.889e-01  5.873e-02   8.325 2.37e-16 ***
pb1064                       -5.825e+00  6.358e+00  -0.916 0.359719
pw1064                        2.449e+01  1.407e+01   1.741 0.082019 .
pm1029                       -1.067e+02  3.206e+01  -3.329 0.000901 ***
pop                          -1.343e+01  1.750e+00  -7.672 3.58e-14 ***
avginc                        6.998e+01  1.291e+01   5.419 7.31e-08 ***
density                       5.980e+00  1.863e+01   0.321 0.748281
shall                        -2.722e+01  7.749e+00  -3.512 0.000461 ***
I(gun.original$incarc_rate^2) -1.486e-04  3.874e-05  -3.835 0.000132 ***
I(gun.original$density^2)    -1.863e+00  1.879e+00  -0.991 0.321653
I(gun.original$rob^2)        -3.633e-04  5.656e-05  -6.424 1.94e-10 ***
I(gun.original$mur^2)        -8.882e-03  2.221e-02  -0.400 0.689279
I(gun.original$avginc^2)     -2.451e+00  4.285e-01  -5.719 1.36e-08 ***
I(gun.original$pb1064^2)      8.615e-02  4.019e-01   0.214 0.830310
I(gun.original$pw1064^2)     -2.366e-01  1.083e-01  -2.185 0.029060 *
I(gun.original$pop^2)         4.112e-01  6.218e-02   6.613 5.74e-11 ***
I(gun.original$pm1029^2)      3.045e+00  9.614e-01   3.168 0.001577 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 95.3 on 1153 degrees of freedom
Multiple R-squared:   0.92,     Adjusted R-squared:  0.9187
F-statistic: 698.3 on 19 and 1153 DF,  p-value: < 2.2e-16
```

Table 2.13 - f-test comparing quadratic model in Table 2.12 to Table 2.2

```
> anova(nonlin.reg.full, nonlin.reg.red)
Analysis of Variance Table

Model 1: gun.original$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall + I(gun.original$incarc_rate^2) +
    I(gun.original$density^2) + I(gun.original$rob^2) + I(gun.original$mur^2) +
    I(gun.original$avginc^2) + I(gun.original$pb1064^2) + I(gun.original$pw1064^2) +
    I(gun.original$pop^2) + I(gun.original$pm1029^2)
Model 2: gun.original$vio ~ mur + rob + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density + shall
  Res.Df      RSS Df Sum of Sq      F    Pr(>F)
1   1153 10471133
2   1162 12708545 -9  -2237413 27.374 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
```

Table 2.14 - full interaction variable model

```
> summary(int.full.reg)

Call:
lm(formula = gun.original$vio ~ . + .^2, data = gun.original)

Residuals:
     Min       1Q   Median       3Q      Max 
-274.945  -49.924   -4.032   48.932  305.882 

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)         -1.701e+03  2.248e+03  -0.756 0.449533    
mur                  1.916e+01  5.379e+01   0.356 0.721757    
rob                  7.249e+00  2.202e+00   3.292 0.001027 ** 
incarc_rate          9.675e-01  1.669e+00   0.580 0.562159    
pb1064              -2.693e+01  6.546e+01  -0.411 0.680888    
pw1064               2.057e+01  3.247e+01   0.634 0.526515    
pm1029              -2.148e+01  1.083e+02  -0.198 0.842761    
pop                  1.015e+02  4.450e+01   2.282 0.022699 *  
avginc               8.901e+01  6.830e+01   1.303 0.192750    
density             -7.654e+02  4.866e+02  -1.573 0.116038    
shall               -3.550e+02  3.033e+02  -1.170 0.242101    
mur:rob             -1.678e-02  7.501e-03  -2.236 0.025532 *  
mur:incarc_rate     -2.281e-02  6.956e-03  -3.279 0.001075 ** 
mur:pb1064          -9.125e-01  1.669e+00  -0.547 0.584585    
mur:pw1064          -5.123e-01  8.158e-01  -0.628 0.530173    
mur:pm1029          -6.404e-01  8.329e-01  -0.769 0.442154    
mur:pop              5.701e-01  3.077e-01   1.852 0.064232 .  
mur:avginc           3.455e+00  7.536e-01   4.584 5.07e-06 ***
mur:density         -1.568e+00  1.007e+00  -1.557 0.119768    
mur:shall           -1.553e+01  4.612e+00  -3.366 0.000788 ***
rob:incarc_rate      1.539e-03  3.970e-04   3.877 0.000112 ***
rob:pb1064           7.139e-02  7.244e-02   0.985 0.324600    
rob:pw1064           3.261e-02  3.571e-02   0.913 0.361336    
rob:pm1029          -2.426e-01  5.262e-02  -4.611 4.48e-06 ***
rob:pop              2.606e-02  8.377e-03   3.111 0.001911 ** 
rob:avginc          -3.326e-01  3.257e-02 -10.212  < 2e-16 ***
rob:density          1.416e-01  4.069e-02   3.482 0.000518 ***
rob:shall            1.091e+00  1.828e-01   5.967 3.24e-09 ***
incarc_rate:pb1064   4.536e-02  5.029e-02   0.902 0.367238    
incarc_rate:pw1064   5.592e-03  2.462e-02   0.227 0.820364    
incarc_rate:pm1029   2.715e-02  2.382e-02   1.140 0.254689    
incarc_rate:pop      1.779e-02  7.696e-03   2.311 0.021010 *  
incarc_rate:avginc  -1.278e-01  2.135e-02  -5.986 2.90e-09 ***
incarc_rate:density -5.630e-02  4.935e-02  -1.141 0.254167    
incarc_rate:shall    9.546e-02  8.597e-02   1.110 0.267076    
pb1064:pw1064        7.942e-01  9.270e-02   8.567  < 2e-16 ***
pb1064:pm1029        2.479e+00  3.108e+00   0.798 0.425210    
pb1064:pop          -1.206e+01  1.593e+00  -7.571 7.72e-14 ***
pb1064:avginc        1.138e-01  1.922e+00   0.059 0.952808    
pb1064:density      -2.976e+01  1.631e+01  -1.825 0.068289 .  
pb1064:shall        -8.823e+00  1.024e+01  -0.861 0.389260    
pw1064:pm1029        5.838e-01  1.574e+00   0.371 0.710760    
pw1064:pop          -4.080e+00  7.061e-01  -5.778 9.79e-09 ***
pw1064:avginc       -7.117e-01  9.301e-01  -0.765 0.444337    
pw1064:density      -9.357e+00  7.671e+00  -1.220 0.222808    
pw1064:shall        -1.852e-01  4.645e+00  -0.040 0.968201    
pm1029:pop           5.499e+00  8.908e-01   6.173 9.33e-10 ***
pm1029:avginc       -2.569e+00  1.386e+00  -1.854 0.064040 .  
pm1029:density       4.519e+01  1.089e+01   4.149 3.59e-05 ***
pm1029:shall         1.553e+01  6.038e+00   2.572 0.010234 *  
pop:avginc           7.926e+00  5.952e-01  13.317  < 2e-16 ***
pop:density         -1.653e+01  5.078e+00  -3.255 0.001169 ** 
pop:shall           -1.642e+00  3.775e+00  -0.435 0.663593    
avginc:density       5.678e+01  6.406e+00   8.863  < 2e-16 ***
avginc:shall         5.710e+00  5.780e+00   0.988 0.323403    
density:shall       -4.916e+01  1.585e+02  -0.310 0.756428    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 80.13 on 1117 degrees of freedom
Multiple R-squared:  0.9452,	Adjusted R-squared:  0.9425 
F-statistic: 350.5 on 55 and 1117 DF,  p-value: < 2.2e-16

> |
```

Table 2.15 - reduced intercept model

```
> summary(red.mod.reg)

Call:
lm(formula = gun.yr.st.dummy$vio ~ 1, data = gun.yr.st.dummy)

Residuals:
    Min      1Q  Median      3Q     Max 
-456.07 -219.97  -60.07  147.83 2418.73 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   503.07       9.76   51.54   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 334.3 on 1172 degrees of freedom
```

Table 2.16 - Full model including all variables

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.617e+03  2.909e+03   1.587 0.112766    
mur          6.369e+01  3.905e+01   1.631 0.103183    
rob         -5.123e+00  1.606e+00  -3.189 0.001468 ** 
incarc_rate  1.204e+00  1.187e+00   1.014 0.310641    
pb1064      -3.551e+02  1.823e+02  -1.948 0.051737 .  
pw1064      -2.154e+02  8.581e+01  -2.510 0.012236 *  
pm1029       1.591e+02  4.790e+01   3.322 0.000925 ***
pop          1.086e+02  4.541e+01   2.393 0.016903 *  
avginc       2.560e+02  6.305e+01   4.060 5.28e-05 ***
density     -3.528e+02  5.646e+02  -0.625 0.532235    
shall       -9.268e+01  1.993e+02  -0.465 0.641977    
stateid_2   -1.068e+02  6.347e+01  -1.682 0.092860 .  
stateid_4    8.382e+01  5.173e+01   1.620 0.105470    
stateid_5   -5.092e+01  3.578e+01  -1.423 0.154935    
stateid_6   -9.441e+01  1.397e+02  -0.676 0.499352    
stateid_8   -6.680e+00  6.516e+01  -0.103 0.918366    
stateid_9    1.143e+02  2.562e+02   0.446 0.655685    
stateid_10  -2.337e+01  1.411e+02  -0.166 0.868439    
stateid_11  -1.548e+02  2.008e+03  -0.077 0.938567    
stateid_12   3.705e+02  6.490e+01   5.709 1.49e-08 ***
stateid_13   4.910e+01  2.862e+01   1.716 0.086528 .  
stateid_15  -9.450e+02  2.285e+02  -4.136 3.82e-05 ***
stateid_16   8.437e+00  9.110e+01   0.093 0.926228    
stateid_17   2.305e+02  6.179e+01   3.731 0.000201 ***
stateid_18   3.492e+01  6.415e+01   0.544 0.586348    
stateid_19  -4.288e+01  8.610e+01  -0.498 0.618543    
stateid_20  -5.186e+01  6.150e+01  -0.843 0.399272    
stateid_21  -2.709e+01  6.355e+01  -0.426 0.669976    
stateid_22   1.320e+02  2.873e+01   4.593 4.91e-06 ***
stateid_23  -3.078e+01  9.438e+01  -0.326 0.744429    
stateid_24   1.534e+02  1.454e+02   1.055 0.291579    
stateid_25   5.512e+02  2.689e+02   2.050 0.040650 *  
stateid_26   1.864e+02  5.529e+01   3.372 0.000774 ***
stateid_27  -1.372e+02  7.887e+01  -1.739 0.082285 .  
stateid_28  -2.873e+02  5.411e+01  -5.310 1.34e-07 ***
stateid_29   3.529e+01  4.885e+01   0.722 0.470246    
stateid_30  -1.328e+02  7.191e+01  -1.847 0.065031 .  
stateid_31  -5.545e+01  7.693e+01  -0.721 0.471181    
stateid_32  -1.556e+02  5.775e+01  -2.694 0.007169 ** 
stateid_33  -6.934e+01  9.600e+01  -0.722 0.470295    
stateid_34   6.021e+02  3.424e+02   1.759 0.078932 .  
stateid_35   1.846e+02  4.938e+01   3.739 0.000195 ***
stateid_36   3.418e+02  1.028e+02   3.325 0.000915 ***
stateid_37   1.084e+02  3.112e+01   3.484 0.000514 ***
stateid_38  -1.656e+02  8.180e+01  -2.024 0.043197 *  
stateid_39   9.145e+01  7.653e+01   1.195 0.232368    
stateid_40  -1.510e+01  3.457e+01  -0.437 0.662396    
stateid_41   1.816e+01  7.372e+01   0.246 0.805502    
stateid_42   9.199e-01  7.914e+01   0.012 0.990728    
stateid_44   3.461e+02  4.047e+02   0.855 0.392688    
```

```
stateid_44                                                      3.461e+02  4.047e+02   0.855 0.392688
stateid_45                                                      1.911e+02  2.577e+01   7.417 2.49e-13 ***
stateid_46                                                     -1.337e+02  6.911e+01  -1.935 0.053225 .
stateid_47                                                      3.281e+01  3.861e+01   0.850 0.395604
stateid_48                                                     -1.572e+00  1.234e+02  -0.013 0.989837
stateid_49                                                     -5.067e+00  8.575e+01  -0.059 0.952887
stateid_50                                                     -4.986e+01  9.524e+01  -0.524 0.600708
stateid_51                                                     -1.149e+02  3.622e+01  -3.173 0.001553 **
stateid_53                                                     -4.457e+00  5.506e+01  -0.081 0.935490
stateid_54                                                     -3.716e+01  8.336e+01  -0.446 0.655827
stateid_55                                                     -1.451e+02  6.877e+01  -2.110 0.035109 *
stateid_56                                                     -1.402e+01  8.616e+01  -0.163 0.870821
year_78                                                         1.039e+00  8.524e+00   0.122 0.903034
year_79                                                         2.258e+01  8.996e+00   2.510 0.012216 *
year_80                                                         3.113e+01  9.544e+00   3.261 0.001146 **
year_81                                                         1.932e+01  1.048e+01   1.844 0.065502 .
year_82                                                         1.508e+01  1.174e+01   1.285 0.199202
year_83                                                         1.319e+00  1.372e+01   0.096 0.923450
year_84                                                         1.415e+00  1.647e+01   0.086 0.931569
year_85                                                         4.510e+00  1.879e+01   0.240 0.810391
year_86                                                         1.703e+01  2.124e+01   0.802 0.422796
year_87                                                         1.055e+01  2.375e+01   0.444 0.657075
year_88                                                         1.762e+01  2.624e+01   0.671 0.502063
year_89                                                         1.985e+01  2.864e+01   0.693 0.488416
year_90                                                         4.148e+01  3.277e+01   1.266 0.205939
year_91                                                         4.626e+01  3.458e+01   1.338 0.181217
year_92                                                         5.737e+01  3.645e+01   1.574 0.115818
year_93                                                         6.383e+01  3.800e+01   1.680 0.093289 .
year_94                                                         5.607e+01  3.965e+01   1.414 0.157618
year_95                                                         4.768e+01  4.112e+01   1.160 0.246436
year_96                                                         3.032e+01  4.238e+01   0.716 0.474439
year_97                                                         3.051e+01  4.358e+01   0.700 0.483978
year_98                                                         2.954e+01  4.489e+01   0.658 0.510659
year_99                                                         1.769e+01  4.603e+01   0.384 0.700903
I(gun.yr.st.dummy$incarc_rate^2)                               -1.332e-04  1.436e-04  -0.927 0.353906
I(gun.yr.st.dummy$density^2)                                    5.372e+00  2.467e+01   0.218 0.827685
I(gun.yr.st.dummy$rob^2)                                       -1.558e-04  2.707e-04  -0.576 0.564938
I(gun.yr.st.dummy$mur^2)                                        8.173e-02  1.251e-01   0.653 0.513771
I(gun.yr.st.dummy$avginc^2)                                     3.821e-01  4.923e-01   0.776 0.437853
I(gun.yr.st.dummy$pb1064^2)                                     7.715e+00  3.031e+00   2.545 0.011059 *
I(gun.yr.st.dummy$pw1064^2)                                     1.828e+00  6.233e-01   2.934 0.003425 **
I(gun.yr.st.dummy$pop^2)                                        1.711e+00  2.679e-01   6.386 2.57e-10 ***
I(gun.yr.st.dummy$pm1029^2)                                    -4.409e+00  1.204e+00  -3.663 0.000262 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$rob)                   -1.067e-02  1.079e-02  -0.989 0.323035
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$incarc_rate)           -2.615e-02  7.217e-03  -3.624 0.000304 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pb1064)                -8.514e-01  1.180e+00  -0.721 0.470883
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pw1064)                -8.361e-01  6.075e-01  -1.376 0.169049
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pm1029)                -9.957e-01  8.128e-01  -1.225 0.220829
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pop)                    9.531e-02  3.067e-01   0.311 0.755998
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$avginc)                 1.389e+00  5.375e-01   2.585 0.009880 **
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$density)               -1.596e+00  8.272e-01  -1.929 0.054001 .
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)                 -2.185e+00  2.856e+00  -0.765 0.444417
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$incarc_rate)            1.015e-03  3.666e-04   2.768 0.005737 **
```

```
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)                    -2.185e+00  2.856e+00  -0.765 0.444417
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$incarc_rate)               1.015e-03  3.666e-04   2.768 0.005737 **
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pb1064)                    2.114e-01  5.539e-02   3.816 0.000144 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pw1064)                    1.214e-01  2.666e-02   4.554 5.90e-06 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pm1029)                   -1.185e-01  4.239e-02  -2.796 0.005271 **
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pop)                       6.701e-03  1.196e-02   0.560 0.575413
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$avginc)                   -4.106e-02  2.523e-02  -1.628 0.103898
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$density)                   1.404e-01  5.841e-02   2.403 0.016436 *
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$shall)                     2.784e-01  1.099e-01   2.534 0.011420 *
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pb1064)            1.504e-03  3.521e-02   0.043 0.965936
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pw1064)            9.313e-03  1.580e-02   0.590 0.555598
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pm1029)           -5.474e-02  2.855e-02  -1.918 0.055417 .
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pop)               2.527e-03  8.573e-03   0.295 0.768230
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$avginc)           -6.800e-02  1.705e-02  -3.988 7.12e-05 ***
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$density)           1.322e-01  4.195e-02   3.151 0.001674 **
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$shall)             1.441e-01  6.103e-02   2.360 0.018443 *
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pw1064)                 7.746e+00  2.643e+00   2.931 0.003453 **
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pm1029)                -3.427e+00  1.254e+00  -2.733 0.006379 **
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pop)                   -1.120e+01  1.825e+00  -6.135 1.21e-09 ***
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$avginc)                -7.813e+00  1.884e+00  -4.147 3.64e-05 ***
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$density)               -8.459e+00  1.434e+01  -0.590 0.555450
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$shall)                 -4.834e+00  6.260e+00  -0.772 0.440178
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$pop)                   -2.058e+00  6.514e-01  -3.160 0.001625 **
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$avginc)                -3.575e+00  9.110e-01  -3.925 9.26e-05 ***
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$density)               -8.891e+00  5.303e+00  -1.677 0.093938 .
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$shall)                 -1.522e+00  2.835e+00  -0.537 0.591512
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$pop)                    1.182e+00  7.924e-01   1.491 0.136235
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$avginc)                 5.615e-01  1.086e+00   0.517 0.605200
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$density)                1.626e+01  9.639e+00   1.687 0.091920 .
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$shall)                  6.483e+00  4.011e+00   1.616 0.106309
I(gun.yr.st.dummy$pop * gun.yr.st.dummy$avginc)                    2.186e+00  5.545e-01   3.942 8.61e-05 ***
I(gun.yr.st.dummy$pop * gun.yr.st.dummy$density)                  -6.033e+01  2.577e+01  -2.341 0.019434 *
I(gun.yr.st.dummy$pop * gun.yr.st.dummy$shall)                    -3.906e+00  2.839e+00  -1.376 0.169183
I(gun.yr.st.dummy$avginc * gun.yr.st.dummy$density)                2.053e+01  4.935e+00   4.160 3.44e-05 ***
I(gun.yr.st.dummy$avginc * gun.yr.st.dummy$shall)                  1.317e+00  3.568e+00   0.369 0.712204
I(gun.yr.st.dummy$density * gun.yr.st.dummy$shall)                 3.854e+02  1.490e+02   2.586 0.009837 **
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pw1064):I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pm1029)  1.275e-03  1.310e-03   0.973 0.330651
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 40.5 on 1036 degrees of freedom
Multiple R-squared:  0.987,	Adjusted R-squared:  0.9853
F-statistic: 579.5 on 136 and 1036 DF,  p-value: < 2.2e-16
```

Table 2.17 - f-test comparing intercept model in Table 2.16 to Table 2.17

```
Model 2: gun.yr.st.dummy$vio ~ 1
  Res.Df       RSS   Df  Sum of Sq      F    Pr(>F)
1   1036   1699312
2   1172 130960737 -136 -129261425 579.45 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

Table 2.18 - Final Model using ‘both’ algorithm starting with intercept model

```
Coefficients:
                                                                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                                                                             -3.870e+02  1.553e+02  -2.492 0.012842 *
rob                                                                                     -5.171e+00  9.593e-01  -5.390 8.62e-08 ***
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pm1029)                                  2.101e-02  9.360e-03   2.244 0.025002 *
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pb1064)                                          1.539e-01  2.594e-02   5.932 4.01e-09 ***
stateid_35                                                                               2.155e+02  1.173e+01  18.380  < 2e-16 ***
stateid_45                                                                               2.075e+02  1.434e+01  14.477  < 2e-16 ***
stateid_12                                                                               2.356e+02  2.108e+01  11.175  < 2e-16 ***
mur                                                                                      5.955e+01  7.976e+00   7.466 1.69e-13 ***
stateid_25                                                                               2.772e+02  1.592e+01  17.413  < 2e-16 ***
stateid_32                                                                              -1.673e+02  2.164e+01  -7.732 2.40e-14 ***
stateid_6                                                                               -7.685e+01  4.199e+01  -1.830 0.067496 .
stateid_51                                                                              -1.511e+02  1.227e+01 -12.314  < 2e-16 ***
stateid_55                                                                              -1.366e+02  1.048e+01 -13.032  < 2e-16 ***
stateid_28                                                                              -2.198e+02  2.421e+01  -9.081  < 2e-16 ***
I(gun.yr.st.dummy$mur^2)                                                                 1.909e-01  7.486e-02   2.551 0.010887 *
stateid_17                                                                               1.014e+02  1.136e+01   8.927  < 2e-16 ***
stateid_8                                                                                2.390e+01  1.214e+01   1.969 0.049197 *
stateid_56                                                                               4.639e+01  1.193e+01   3.890 0.000106 ***
stateid_16                                                                               5.363e+01  1.069e+01   5.019 6.07e-07 ***
stateid_37                                                                               5.994e+01  1.133e+01   5.290 1.48e-07 ***
stateid_22                                                                               1.215e+02  1.488e+01   8.166 8.76e-16 ***
I(gun.yr.st.dummy$avginc * gun.yr.st.dummy$density)                                      2.183e+01  3.114e+00   7.011 4.15e-12 ***
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$shall)                                       -1.426e+00  4.565e-01  -3.123 0.001836 **
stateid_53                                                                              -1.654e+01  1.170e+01  -1.413 0.157827
stateid_39                                                                              -7.046e+01  1.187e+01  -5.938 3.89e-09 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$shall)                                           3.815e-01  7.274e-02   5.245 1.88e-07 ***
stateid_42                                                                              -1.566e+02  1.484e+01 -10.554  < 2e-16 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pm1029)                                         -3.674e+00  3.570e-01 -10.290  < 2e-16 ***
I(gun.yr.st.dummy$pop^2)                                                                 1.022e+00  1.130e-01   9.042  < 2e-16 ***
stateid_4                                                                                8.608e+01  1.124e+01   7.657 4.20e-14 ***
stateid_26                                                                               8.852e+01  1.074e+01   8.241 4.87e-16 ***
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pop)                                    -6.822e-03  3.472e-03  -1.965 0.049644 *
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$avginc)                                 -4.856e-02  7.402e-03  -6.561 8.26e-11 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)                                          -4.902e+00  1.765e+00  -2.778 0.005565 **
stateid_21                                                                              -3.062e+01  1.060e+01  -2.888 0.003950 **
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pw1064)                                  7.031e-03  3.030e-03   2.321 0.020477 *
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pw1064)                                       5.486e-01  1.752e-01   3.131 0.001788 **
pb1064                                                                                   5.074e+01  1.509e+01   3.362 0.000802 ***
stateid_30                                                                              -9.464e+01  1.038e+01  -9.115  < 2e-16 ***
stateid_38                                                                              -1.155e+02  1.132e+01 -10.203  < 2e-16 ***
stateid_27                                                                              -9.514e+01  1.251e+01  -7.606 6.12e-14 ***
stateid_46                                                                              -8.653e+01  1.199e+01  -7.216 1.00e-12 ***
stateid_54                                                                              -4.083e+01  1.109e+01  -3.681 0.000244 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$pw1064)                                          8.798e-02  1.305e-02   6.741 2.55e-11 ***
year_83                                                                                 -1.017e+01  6.293e+00  -1.617 0.106248
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pop)                                         -1.018e+01  1.020e+00  -9.984  < 2e-16 ***
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$shall)                                        3.923e+00  2.061e+00   1.903 0.057275 .
stateid_5                                                                               -4.557e+01  1.088e+01  -4.188 3.05e-05 ***
year_93                                                                                  2.877e+01  6.611e+00   4.352 1.47e-05 ***
stateid_41                                                                               3.774e+01  1.149e+01   3.284 0.001056 **
```

```
stateid_41                                                                               3.774e+01  1.149e+01   3.284 0.001056 **
year_92                                                                                  2.558e+01  6.512e+00   3.928 9.12e-05 ***
stateid_49                                                                               2.355e+01  1.083e+01   2.175 0.029866 *
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$density)                                 7.020e-02  2.474e-02   2.838 0.004627 **
year_94                                                                                  2.004e+01  6.571e+00   3.049 0.002349 **
year_79                                                                                  1.926e+01  6.522e+00   2.953 0.003213 **
year_80                                                                                  2.223e+01  6.613e+00   3.361 0.000803 ***
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pm1029)                                      -2.276e+00  5.260e-01  -4.326 1.66e-05 ***
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$avginc)                                       6.852e-01  2.112e-01   3.244 0.001214 **
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$density)                                      1.737e+01  5.090e+00   3.413 0.000667 ***
stateid_44                                                                               2.793e+02  2.331e+01  11.981  < 2e-16 ***
stateid_15                                                                              -5.393e+02  1.436e+02  -3.756 0.000182 ***
I(gun.yr.st.dummy$pop * gun.yr.st.dummy$avginc)                                          1.337e+00  2.728e-01   4.900 1.10e-06 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$incarc_rate)                                     1.422e-03  1.473e-04   9.657  < 2e-16 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$incarc_rate)                                    -3.256e-02  3.663e-03  -8.889  < 2e-16 ***
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$pop)                                         -2.186e+00  4.300e-01  -5.082 4.39e-07 ***
pop                                                                                      1.565e+02  3.317e+01   4.720 2.67e-06 ***
pw1064                                                                                   5.312e+00  2.212e+00   2.401 0.016510 *
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$rob)                                            -2.165e-02  5.262e-03  -4.115 4.17e-05 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$density)                                         8.809e-02  2.623e-02   3.359 0.000810 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pb1064)                                          7.602e-01  2.759e-01   2.755 0.005970 **
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$avginc)                                          6.953e-01  2.472e-01   2.813 0.005003 **
stateid_34                                                                               9.425e+01  1.772e+01   5.318 1.27e-07 ***
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$density)                                     -1.269e+01  1.649e+00  -7.693 3.21e-14 ***
I(gun.yr.st.dummy$avginc^2)                                                             -2.875e-01  1.068e-01  -2.693 0.007197 **
year_84                                                                                 -8.500e+00  6.188e+00  -1.374 0.169843
stateid_20                                                                              -1.615e+01  1.005e+01  -1.607 0.108318
stateid_2                                                                               -8.249e+01  2.123e+01  -3.885 0.000109 ***
year_99                                                                                 -1.102e+01  7.133e+00  -1.545 0.122548
year_90                                                                                  1.483e+01  6.437e+00   2.304 0.021411 *
year_91                                                                                  1.495e+01  6.561e+00   2.278 0.022910 *
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$density)                                     -1.829e+01  4.023e+00  -4.546 6.09e-06 ***
year_95                                                                                  1.187e+01  6.593e+00   1.800 0.072081 .
year_81                                                                                  1.135e+01  6.562e+00   1.730 0.083867 .
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$density)                                        -1.064e+00  5.935e-01  -1.793 0.073178 .
stateid_29                                                                               1.921e+01  1.106e+01   1.737 0.082639 .
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pw1064):I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pm1029)  9.053e-04  5.364e-04   1.688 0.091745 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 40.88 on 1087 degrees of freedom
Multiple R-squared:  0.9861,    Adjusted R-squared:  0.985
F-statistic: 909.2 on 85 and 1087 DF,  p-value: < 2.2e-16
```

Table 2.19 - summary of shall-issue related results for first iteration of final model

```
#################### significant findings related to shall laws in order of addition to the model ###########################
#I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$shall)          coef = -1.426e+00;  SE = 4.565e-01;  t-stat = -3.123;  p-val = 0.001836 **
#I(gun.yr.st.dummy$rob * gun.yr.st.dummy$shall)             coef = 3.815e-01;   SE = 7.274e-02;  t-stat =  5.245;  p-val = 1.88e-07 ***
#I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)             coef = -4.902e+00;  SE = 1.765e+00;  t-stat = -2.778;  p-val = 0.005565 **
#I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$shall)          coef = 3.923e+00;  SE =  2.061e+00;  t-stat = 1.903;  p-val = 0.057275 .

# interestingly, shall itself does not appear as a standalone varaible. shall is only significant in this model when interacted with other variables.
# this could mean that shall laws are only significant under certain demographic conditions.
# however, not all of these variables are negative. Although relatively small and insignificant, shall's interaction with robbery and with pm1029 both have positive effects!
# if shall laws have positive contributions to violence in some demographic contexts, that could indicate that there are negative, un-intended consequences from shall laws.
# According to this model, when shall laws are implemented where pw1064 is relatively higher, violent crime seems to be significantly reduced. However, this may be more
# corrolary than causal.Additionally, shall laws seem to reduce violent crime when there are relatively high murder rates in certain states.
# however, shall laws seem to increase the amount of violent crime when there are more robberies in certain states. This may be because robbers are more inclined to rob
# someone when they have confidence that their victim will not be armed due to the fact that there are laws prohibiting many people from having weapons. this increased likelihood
# to rob people will naturally result in more violent crimes. finally, the least significant variable is the interaction between pm1029 and whether there is shall laws in a certain state.
# interestingly, this variable is positive indicating that shall laws increase the number of violent crimes in areas where the pm1029 is relatively higher. this may be due to similar reasons per above.
# young males are more likely to commit robberies. so, if those young males expect their victims to be unarmed, they are more likely to attempt a crime. then, it would make sense that with more robbery attempts,
# there will also be more violent crimes as there are more of those sorts of interactions.
# Again, this data can only provide insight into relationships and may not necessarily be causal. However, it does provide insight into the relationships between these variables.
```

Table 2.20 - Final Fixed Effects Model Maximized for AIC, BIC, and minimizing Adj.R^2

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.201e+03	2.994e+02	-4.011	6.46e-05	***
mur	-4.523e+01	1.743e+01	-2.595	0.009577	**
rob	8.262e-01	1.715e-01	4.818	1.66e-06	***
incarc_rate	1.569e+00	3.639e-01	4.313	1.76e-05	***
pm1029	1.357e+02	3.319e+01	4.088	4.68e-05	***
avginc	2.918e+01	9.206e+00	3.169	0.001572	**
density	-8.031e+02	8.061e+01	-9.963	< 2e-16	***
stateid_2	-1.638e+02	2.981e+01	-5.493	4.92e-08	***
stateid_5	-1.229e+02	1.303e+01	-9.434	< 2e-16	***
stateid_8	-7.934e+01	1.575e+01	-5.038	5.53e-07	***
stateid_9	-1.917e+02	1.515e+01	-12.654	< 2e-16	***
stateid_10	-1.591e+02	2.116e+01	-7.519	1.16e-13	***
stateid_11	1.023e+03	1.710e+02	5.981	3.02e-09	***
stateid_12	2.859e+02	2.599e+01	10.998	< 2e-16	***
stateid_13	6.261e+01	1.878e+01	3.333	0.000887	***
stateid_15	-3.298e+02	4.000e+01	-8.246	4.73e-16	***
stateid_16	-1.183e+02	1.829e+01	-6.464	1.54e-10	***
stateid_17	1.323e+02	1.855e+01	7.131	1.83e-12	***
stateid_18	-7.959e+01	1.750e+01	-4.549	6.01e-06	***
stateid_19	-1.520e+02	1.942e+01	-7.828	1.18e-14	***
stateid_20	-1.499e+02	1.389e+01	-10.794	< 2e-16	***
stateid_21	-1.302e+02	1.388e+01	-9.380	< 2e-16	***
stateid_22	1.485e+02	1.598e+01	9.292	< 2e-16	***
stateid_23	-1.632e+02	2.189e+01	-7.457	1.82e-13	***
stateid_25	1.114e+02	1.393e+01	8.001	3.17e-15	***
stateid_26	1.051e+02	1.668e+01	6.297	4.41e-10	***
stateid_27	-2.184e+02	2.034e+01	-10.737	< 2e-16	***
stateid_28	-1.768e+02	1.819e+01	-9.721	< 2e-16	***
stateid_29	-3.882e+01	1.315e+01	-2.952	0.003222	**
stateid_30	-2.519e+02	1.678e+01	-15.010	< 2e-16	***
stateid_31	-1.689e+02	1.738e+01	-9.720	< 2e-16	***
stateid_32	-2.427e+02	1.905e+01	-12.738	< 2e-16	***
stateid_33	-2.091e+02	2.319e+01	-9.017	< 2e-16	***
stateid_35	9.676e+01	1.409e+01	6.866	1.11e-11	***
stateid_36	7.536e+01	2.341e+01	3.219	0.001327	**
stateid_37	9.307e+01	1.680e+01	5.540	3.80e-08	***
stateid_38	-3.058e+02	1.997e+01	-15.316	< 2e-16	***
stateid_39	-6.319e+01	1.926e+01	-3.281	0.001068	**
stateid_40	-8.008e+01	1.120e+01	-7.152	1.58e-12	***
stateid_41	-6.814e+01	1.671e+01	-4.078	4.87e-05	***
stateid_42	-1.481e+02	2.232e+01	-6.637	5.06e-11	***
stateid_45	2.203e+02	1.347e+01	16.350	< 2e-16	***
stateid_46	-2.606e+02	1.739e+01	-14.984	< 2e-16	***
stateid_47	-3.218e+01	1.206e+01	-2.668	0.007746	**
stateid_48	1.079e+02	2.651e+01	4.069	5.06e-05	***
stateid_49	-1.426e+02	1.812e+01	-7.870	8.58e-15	***
stateid_50	-1.882e+02	2.226e+01	-8.456	< 2e-16	***
stateid_51	-1.622e+02	1.489e+01	-10.891	< 2e-16	***
stateid_53	-8.822e+01	1.605e+01	-5.497	4.82e-08	***
stateid_54	-1.771e+02	1.888e+01	-9.381	< 2e-16	***
stateid_55	-2.384e+02	1.729e+01	-13.787	< 2e-16	***
stateid_56	-1.319e+02	1.760e+01	-7.495	1.38e-13	***

```
year_79                                                      2.220e+01  6.630e+00   3.348 0.000842 ***
year_80                                                      3.018e+01  6.853e+00   4.403 1.17e-05 ***
year_81                                                      1.979e+01  6.786e+00   2.917 0.003607 **
year_82                                                      1.670e+01  6.648e+00   2.512 0.012147 *
year_86                                                      1.631e+01  7.482e+00   2.180 0.029497 *
year_87                                                      1.204e+01  8.122e+00   1.482 0.138647
year_88                                                      1.982e+01  8.862e+00   2.236 0.025553 *
year_89                                                      2.422e+01  9.643e+00   2.511 0.012173 *
year_90                                                      4.517e+01  1.048e+01   4.311 1.77e-05 ***
year_91                                                      5.469e+01  1.125e+01   4.861 1.34e-06 ***
year_92                                                      6.669e+01  1.187e+01   5.621 2.42e-08 ***
year_93                                                      7.558e+01  1.252e+01   6.036 2.17e-09 ***
year_94                                                      7.021e+01  1.315e+01   5.338 1.15e-07 ***
year_95                                                      6.197e+01  1.376e+01   4.504 7.41e-06 ***
year_96                                                      4.595e+01  1.435e+01   3.203 0.001402 **
year_97                                                      4.660e+01  1.484e+01   3.140 0.001737 **
year_98                                                      4.258e+01  1.562e+01   2.726 0.006511 **
year_99                                                      3.131e+01  1.633e+01   1.917 0.055446 .
I(gun.yr.st.dummy$pm1029^2)                                 -3.590e+00  9.395e-01  -3.821 0.000140 ***
I(gun.yr.st.dummy$avginc * gun.yr.st.dummy$density)          2.285e+01  2.498e+00   9.147  < 2e-16 ***
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$avginc) -4.750e-02  9.257e-03  -5.131 3.42e-07 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$shall)               2.720e-01  8.966e-02   3.034 0.002473 **
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pm1029) -5.459e-02  1.853e-02  -2.946 0.003288 **
I(gun.yr.st.dummy$pop * gun.yr.st.dummy$avginc)              1.668e+00  3.647e-01   4.574 5.33e-06 ***
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pop)             -8.801e+00  1.246e+00  -7.062 2.94e-12 ***
I(gun.yr.st.dummy$pop^2)                                     1.586e+00  1.460e-01  10.865  < 2e-16 ***
I(gun.yr.st.dummy$incarc_rate^2)                            -2.236e-04  7.530e-05  -2.969 0.003051 **
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pw1064)              1.274e+00  2.405e-01   5.296 1.43e-07 ***
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$density)          1.746e+01  2.891e+00   6.037 2.16e-09 ***
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$incarc_rate)         1.219e-03  1.408e-04   8.658  < 2e-16 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pb1064)              3.018e+00  5.047e-01   5.979 3.06e-09 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$rob)                -9.947e-03  2.212e-03  -4.497 7.64e-06 ***
I(gun.yr.st.dummy$density * gun.yr.st.dummy$shall)          1.932e+02  7.667e+01   2.519 0.011906 *
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$shall)       1.150e-01  3.903e-02   2.947 0.003278 **
shall                                                       -2.227e+02  5.201e+01  -4.283 2.01e-05 ***
I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$shall)            9.885e+00  3.037e+00   3.255 0.001170 **
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$pm1029)             -2.611e+00  4.268e-01  -6.118 1.33e-09 ***
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$incarc_rate)        -1.727e-02  3.850e-03  -4.485 8.07e-06 ***
I(gun.yr.st.dummy$pw1064 * gun.yr.st.dummy$pop)             -1.162e+00  3.593e-01  -3.233 0.001261 **
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pw1064)           7.497e-01  1.082e-01   6.928 7.35e-12 ***
I(gun.yr.st.dummy$pb1064 * gun.yr.st.dummy$pm1029)          -6.207e-01  1.710e-01  -3.631 0.000296 ***
I(gun.yr.st.dummy$avginc^2)                                 -7.341e-01  3.294e-01  -2.228 0.026074 *
I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)              -4.475e+00  1.975e+00  -2.265 0.023684 *
I(gun.yr.st.dummy$rob * gun.yr.st.dummy$avginc)              2.425e-02  1.234e-02   1.966 0.049541 *
pop                                                          5.452e+01  2.809e+01   1.941 0.052533 .
I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$pop)        -5.122e-03  3.490e-03  -1.468 0.142455
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 41.03 on 1075 degrees of freedom
Multiple R-squared:  0.9862,	Adjusted R-squared:  0.9849
F-statistic:   791 on 97 and 1075 DF,  p-value: < 2.2e-16
```

Table 2.21 - significant variables involving shall from regression in Table 2.20

```
# analysis of results from second itreration of this model

# I(gun.yr.st.dummy$rob * gun.yr.st.dummy$shall)           2.720e-01  8.966e-02   3.034 0.002473 **
# I(gun.yr.st.dummy$density * gun.yr.st.dummy$shall)       1.932e+02  7.667e+01   2.519 0.011906 *
# I(gun.yr.st.dummy$incarc_rate * gun.yr.st.dummy$shall)   1.150e-01  3.903e-02   2.947 0.003278 **
# shall                                                   -2.227e+02  5.201e+01  -4.283 2.01e-05 ***
# I(gun.yr.st.dummy$pm1029 * gun.yr.st.dummy$shall)        9.885e+00  3.037e+00   3.255 0.001170 **
# I(gun.yr.st.dummy$mur * gun.yr.st.dummy$shall)          -4.475e+00  1.975e+00  -2.265 0.023684 *      ############ in this model, but not the below one

# interesting findings from above methodology which removed some variables as they were seen as less valuable for the model
# shall as a standalone variable was very significant, and so was its interaction with various other variables. this indicates that there are
# complex effects from the implementation of shall laws, or that there are specific aspects of states that tend to implement those shall laws.
# This may simply be an insight into the types of states which implement shall laws as opposed to causal effects from shall laws being implemented
# for example, interpretation could read that shall laws increase violence when x, or that shall laws tend to be implemented in areas where x is the case
```