On The Association Of Laws With Gun Violence And Trafficking

Maxwell Lovig

December 17 2023

Abstract

The goal of this report is to survey the status of gun violence and gun trafficking in america and designate which legislative action are most impactful to its value. Our data is source from the ATF and the Gun Violence Association. We present some high-level visualizations on how State Gun Laws evolved and the state of Gun trafficking/Violence from the year 2014 to 2019. Through the use of poissonian GLMs with lasso penalty we state 10 or so important laws which are correlated with a increase/decrease in gun trafficking or violence. Each of these models give a list of laws weighted by their impact that could give legislatures a jumping off point to try to reduce gun violence. Throughout we give commentary on the phenomena we discover.

Executive Summary

The goal of this report is to find which laws have the most likely impact on changing the dynamics of Gun Violence and Gun trafficking the the US. We start by giving visualization to start as a baseline analysis for how diverse and widespread the issues of gun violence and trafficking in America are. To summarize our results we find that the following laws (Alongside a description from a codebook, the law is present if the description is true for a state) are most impactful in understanding the dynamics of 4 different problems. These are ranked by a metric described in the report. For gun trafficking, each law increases the number of guns going entering a state when this law is present in that given state and not present in others (thus suggesting it is a law people circumvent by obtaining an out of state gun, or if it has a (-) it represents the opposite effect, reducing out of state trafficking if the source state has the law but the target state does not. See Modeling and visualizing gun trafficking section for more details on interpretation). For Gun violence we will include a (+) or (-) if the law increases of decreases gun violence.

Gun trafficking under the assumption that each states dynamics only changes with total population:

- **IMMUNITY**: NO LAW PROVIDES IMMUNITY TO OR PROHIBITS LAWSUITS AGAINST GUN MANUFACTURERS
- **DVROSURRENDERCONDITIONS**: STATE LAW REQUIRES RESTRAINING ORDER SUBJECTS TO SURRENDER THEIR FIREARMS
- **JUNKGUN**: BAN ON JUNK GUNS (SOMETIMES CALLED SATURDAY NIGHT SPECIALS)
- **RECORDSALLH**: ALL SELLERS ARE REQUIRED TO KEEP AND RETAIN RECORDS OF HANDGUN SALES
- **ONEPERMONTH**: BUYERS CAN PURCHASE NO MORE THAN ONE HANDGUN PER MONTH WITH LIMITED EXCEPTIONS
- **SHOWING**: APPLICANTS ARE REQUIRED TO MAKE A HEIGHTENED SHOWING FOR CONCEALED CARRY PERMIT
- **BACKGROUNDPURGE**: STATE CAN RETAIN BACKGROUND CHECK RECORDS FOR AT LEAST 60 DAYS
- **PERMITH**: A LICENSE OR PERMIT IS REQUIRED TO PURCHASE HANDGUNS
- **RECORDSALL**: ALL SELLERS ARE REQUIRED TO KEEP AND RETAIN RECORDS OF ALL FIREARM SALES

Gun trafficking under the assumption that each state dynamics are unique:

- **GVRO**: RED FLAG LAW ? PROCESS CAN BE INITIATED BY FAMILY MEMBERS OR LAW ENFORCEMENT
- **PERMIT**: A LICENSE OR PERMIT IS REQUIRED TO PURCHASE ALL FIREARMS
- **LOSTSTOLEN**: MANDATORY REPORTING OF LOST AND STOLEN GUNS BY FIREARM OWNERS
- **MICROSTAMP (-)**: ALL HANDGUNS SOLD MUST HAVE EITHER BALLISTIC FINGERPRINTING OR MICROSTAMPING
- **AMMLICENSE**: VENDOR LICENSE REQUIRED TO SELL AMMUNITION
- **MCDVSURRENDERCONDITIONS**: NO CONDITIONS ON SURRENDER REQUIREMENT FOR DOMESTIC VIOLENCE MISDEMEANANTS
- **PERMITCONCEALED**: PERMIT REQUIRED TO CARRY CONCEALED WEAPONS
- **AGE21LONGUNSALED**: PURCHASE OF LONG GUNS FROM LICENSED DEALERS RESTRICTED TO AGE 21 AND OLDER
- **DANGER (-)**: FIREARM POSSESSION PROHIBITED IF PERSON IS DEEMED BY COURT TO BE A DANGER

Gun violence for low violence counties (less than 50 people injured or killed per year):

- **REPORTALL(-)**: ALL SELLERS ARE REQUIRED TO REPORT ALL FIREARM SALES RECORDS TO THE STATE
- **COLLEGECONCEALED (+)**: NO GUN CARRYING ON COLLEGE CAMPUSES, INCLUDING

CONCEALED WEAPONS PERMITTEES

- **UNIVERSAL (-)**: UNIVERSAL BACKGROUND CHECKS REQUIRED AT POINT OF PURCHASE FOR ALL FIREARMS
- **CAPACCESS (-)**: CRIMINAL LIABILITY FOR NEGLIGENT STORAGE OF GUNS IF CHILD GAINS ACCESS
- **IMMUNITY (-)**: NO LAW PROVIDES IMMUNITY TO OR PROHIBITS LAWSUITS AGAINST GUN MANUFACTURERS
- **ALCOHOLISM** (+): FIREARM POSSESSION IS PROHIBITED FOR SOME PEOPLE WITH ALCOHOLISM
- **AGE18LONGGUNPOSSESS (-)**: PURCHASE OF LONG GUNS FROM ALL SELLERS RESTRICTED TO AGE 18 AND OLDER
- **MENTAL HEALTH (-)**: BACKGROUND CHECKS REQUIRE A SEARCH OF STATE MENTAL HEALTH RECORDS
- **FINGERPRINT (-)**: BUYERS MUST BE FINGERPRINTED AT POINT OF PURCHASE
- **COLLEGE** (+): NO GUN CARRYING ON COLLEGE CAMPUSES EXCEPT FOR CONCEALED WEAPON PERMITTEES
- **OPENCARRYH** (+): NO OPEN CARRY OF HANDGUNS IS ALLOWED IN PUBLIC PLACES

Gun violence for high violence counties (more than 50 people injured or killed per year):

- **AMMPERMIT** (+) : PERMIT REQUIRED TO PURCHASE AMMUNITION
- **REGISTRATIONH (-)**: GUN OWNERS MUST REGISTER THEIR HANDGUNS WITH THE STATE
- **AGE18LONGGUNPOSSESS (-)**": NO POSSESSION OF LONG GUNS UNTIL AGE 18
- **UNIVERSAL (-)**: UNIVERSAL BACKGROUND CHECKS REQUIRED AT POINT OF PURCHASE FOR ALL FIREARMS
- **PREEMPTIONARROW (-)**: ANY STATE LAW THAT PREEMPTS LOCAL REGULATION OF FIREARMS IS NARROW IN ITS SCOPE
- **EXPARTE (-)**: TEMPORARY RESTRAINING ORDER SUBJECTS ARE PROHIBITED FROM POSSESSING FIREARMS
- **PERSONALIZED** (+): STATE HAS A LAW THAT REQUIRES REVIEW OF PERSONALIZED GUN TECHNOLOGY
- **WAITINGH** (+): WAITING PERIOD IS REQUIRED ON ALL HANDGUN PURCHASES FROM DEALERS
- **LOCKSTANDARDS (-)**: SAFETY LOCK IS REQUIRED FOR HANDGUNS AND MUST BE APPROVED BY STATE STANDARDS
- **CAPACCESS (-)**: CRIMINAL LIABILITY FOR NEGLIGENT STORAGE OF GUNS IF CHILD GAINS ACCESS
- **AMMBACKGROUND** (+): BACKGROUND CHECKS REQUIRED FOR AMMUNITION PURCHASE

Introduction

Gun violence is one of the most damning problems plaguing American society. Many Americans have to face the tragedy of loved ones gone for, what should be, a preventable problem. One major issues stopping the progression of is due to the dichotomy of the two major US political parties and how they think guns should be legislated, each believing their side is more effective. This report aims to try to clear some of these issues up by using a data-driven approach to discovering the most impactful gun laws when controlling for external variables. Along the way we try to better understand the dynamics of gun-legislation through the use of visualizations. As a quick tour of this report:

- We describe where our data was sources and how we transformed them for our purposes (See **Constructing Our Datasets**)
- We discuss the overall status of gun violence and gun trafficking using visualizations (See **Visualizing The Changes in State Gun Laws**, **Visualizing Gun Trafficking across state lines**, **Visualizing Gun Violence Incidents Versus Social and Legal Factors**)
- We model our data using poissionian GLM's with a Lasso penalty
- We filter the 10 or so longest staying laws in term of the Lasso penalty and relay them to the reader as the most impactful laws for each model
- We also present diagnostics on each model to better help future work. (For the Last 3 points see **Modeling/Analysis**)

It is our hope that this report gives a little bit of everything and you enjoy reading it.

Constucting Our Datasets

In this section we describe the sources of our data and how we compiled them for convenience in the visualization and modelling below. Our first data set involve trying to model gun traffic across state lines. The department of Alcohol, Tobacco and Firearms is a federal agency which is responsible for investigating and preventing firearm violence, bombings and arson. Year over year they have traced guns from the state of recovery to the state of origin. This dataset will be useful to help us understand the mechanisms for why guns are brought across state boarder and what laws encourage these bad actors to do so.

As an example for the data we are handling, here are the traces for 10 states in the year 2014. The states on the rows refer to the origin/source state (i.e where the gun originated from) and the columns refer to the recovery/target state (i.e. where the gun was found)

Table 1: Traces for the first 6 states in 2014.

NA	ALABAMA	ALASKA	ARIZONA	ARKANSAS	CALIFORNIA	COLORADO
ALABAMA	3561	1	11	6	81	16
ALASKA	3	434	17	0	61	5
ARIZONA	6	5	4544	3	1184	45
ARKANSAS	7	0	21	487	97	11
CALIFORNIA	21	16	193	5	15169	71
COLORADO	3	7	47	0	189	1762

Just to solidify our understanding, the number of guns found in California that are from Arizona in origin is 1184.

There are two issues with this data structure. One is the inconsistent labeling of state / provinces. The second is that this is hard to work with in a tradition modelling scheme. We address these issues by constructing a slightly different data structure. First we unified the row and column names of each of the trace matrices for each year. Secondly, we strip off each element of the matrix into a new row. Here is an example row with this new formatting.

Next we need some information about the gun control laws for a given state per year. This dataset originated from Michael Siegel at Boston University. It contains 134 instances of firearm safety laws and records the

Table 2: The second row of our reformatted data

year	s_name	t_name	flow
2014	ALABAMA	ALASKA	1

presence or absence of these provisions for each state from the years 1990 to 2019 (of which the last 5 years is the most relevant to our study). Just to give some examples for what these laws are, here are 10 keywords which are described in this codebook.

```
[1] "RELINQUISHMENT"  "REPORTALL"       "AMMRECORDS"      "AMMPERMIT"
[5] "AMM18"           "THREEDAYLIMIT"   "ASSAULTTRANSFER" "MICROSTAMP"
[9] "PERMITCONCEALED" "LOCKP"
```

Now we will simply left_join with our previous dataset based on the state and year which is shared between our laws and traces datasets. Since we have two states in each row of our traces dataframe, we have *s_cat* refer to a category for the source state and *t_cat* for a target state. We also calculate the great_circle distance between state centroids and grab the population for both state. Thus we are left with a final dataset, which (up to extra law columns looks like):

Table 3: Random row of our finished traces dataset

year	s_name	t_name	s_pop	t_pop	s_FELONY	t_FELONY	distance	flow
2014	SOUTH CAROLINA	WYOMING	4826858	583159	0	1	28.20804	1

We will analyze this dataset later, in the mean time we construct the second dataset needed for our analysis. Here we start with pulling socio-ecnomic variables from the ACS5 dataset. Using the TidyCensus package we can set up an API key and easily make queries for our data. We will consider the following variables for our dataset (these can be references using the ACS5 codebook).

Table 4: Chosen Varaibles along side their description according to the ACS 5 codebook

variables	description	codename
B01001_001E	Total Population	Tot_pop
B01002_001E	Median Age	Med_age
B06011_001E	Median Income (adj)	Med_inc
B17001_001E	Income Below Poverty Level (total)	PL_tot
B17001_002E	Income Below Poverty Level (est)	PL_est
B22001_001E	Recieved Food Stamps (total)	FS_tot
B22001_002E	Recieved Food Stamps (est)	FS_est
B23025_003E	Employment Force (total)	ES_tot
B23025_004E	Employed (est)	ES_est
B25003_001E	Total Tenure	Tot_ten
B25003_003E	Rented Tenure	Ren_ten
B25064_001E	Median Gross Rent	Med_rent
B25077_001E	Median Net Worth	Med_net

Notice that this collection of variables is race and gender blind, this was done intentionally. The goal of this analysis is to give guidance to local communities on economic issues that can possibly be addressed if it is impossible to change gun legislature in the near future. Although it may improve predictive performance, the effect sizes for race/gender in this model are functionally useless. The goal is to provide actionable change to reduce the number of gun violence deaths, stating that a larger proportion of a race or gender leads to more gun violence is unobjectionable and overtly biased.

Next we need data corresponding to incidents of gun violence in the united states. Thankfully this has been recorded by the gun violence archive, a not for profit corporation which provides near-real time tracking of gun violence in America. I was in contact with people from the GVA and was able to receive all but one year of Gun data needed for my analysis. I was able to pull the remaining year from a previous scrape of the data found on this github. We can put these sources together and have each gun violence instance be tied to a location, date and description. Such an example for a row of this data can be seen by:

Table 5: 5 sample rows for the GVA data

date	state	city_or_county	address	latitude	longitude	n_killed	n_injured
2016-12-31	Virginia	Newport News	Vernon Place	37.0186	-76.4332	0	1
2016-12-31	Tennessee	Knoxville	Highland View Drive	35.8859	-83.8147	1	0
2016-12-31	Florida	Pensacola	3 Talladega Trail	30.4375	-87.2821	0	1
2016-12-31	Maryland	Baltimore	4600 block of Reistertown Rd	39.3402	-76.6715	0	1
2016-12-31	Nebraska	Omaha	2501 N 38th St	41.2814	-95.9703	0	1

Using the latitude and longitudes for each of these points we can then generate the unique GEOID for each of these incidents. When can then left_joint this dataset with the social variables by GEOID (Country + State + tract) and year. We then do one more left_join to the laws by state and year.

As a last step we will now normalize some of the values from our social data which we drew both the estimate and the total from.

This gives us our final data frame which we can then move on to visualizations and modelling.

Visualizing The Changes in State Gun Laws

As mentioned previously there are 137 total laws which have been recorded from each US state since 1991. As mentioned previously, there are many possible laws that can be explanations for an increase in gun violence / trafficking. Unfortunately, with a lack of domain expertise we have to look at a more mathematical way to understand how these variables are best fit for our modelling.

At first glance there are immediate issues with how many laws there are. Intrinsically we believe that each law should affect the dynamics of gun-violence in some way but because of the number of laws, this is already quite complicated. Each law has a diverse meaning and it is hard to understand how these will operate in a 137 dimensional space. Beyond purely dimensional issues there are going to be laws which are highly correlated. The extreme of which can be immediately seen as some laws which have complete overlap.

The groups with complete overlap are:

Table 6: The Laws with complete overlap

Group	Contents
1	VIOLENT , VIOLENTH
2	RESIDENTIAL , AGE21LONGGUNPOSSESS , LOCKED
3	THEFT , TRAFFICKINGBACKGROUND , STRAWPURCHASE
4	AMMPERMIT , AMMBACKGROUND
5	AGE21LONGGUNSALED , AGE21LONGGUNSALE
6	ASSAULT , ASSAULTLIST
7	CAPUSES , CAP14
8	EXPARTESURRENDERNOCONDITIONS , EXPARTESURRENDERDATING

This immediately raises a question of how to distribute the impact of laws which occur in perfect co-linearity. Even beyond these laws with perfect correlation we also have to keep track of how often specific laws are related to one another. When we attempt to give recommendations on specific laws which may lead to decreases in violence it is important to understand that it is not trivial to simply change one law in isolation. To see how complex this correlation structure is we plot the correlation matrix between laws. We also reordered the columns to cluster laws which are strongly correlated together. Notice that laws occur in clusters will show up as blocks on the diagonal.

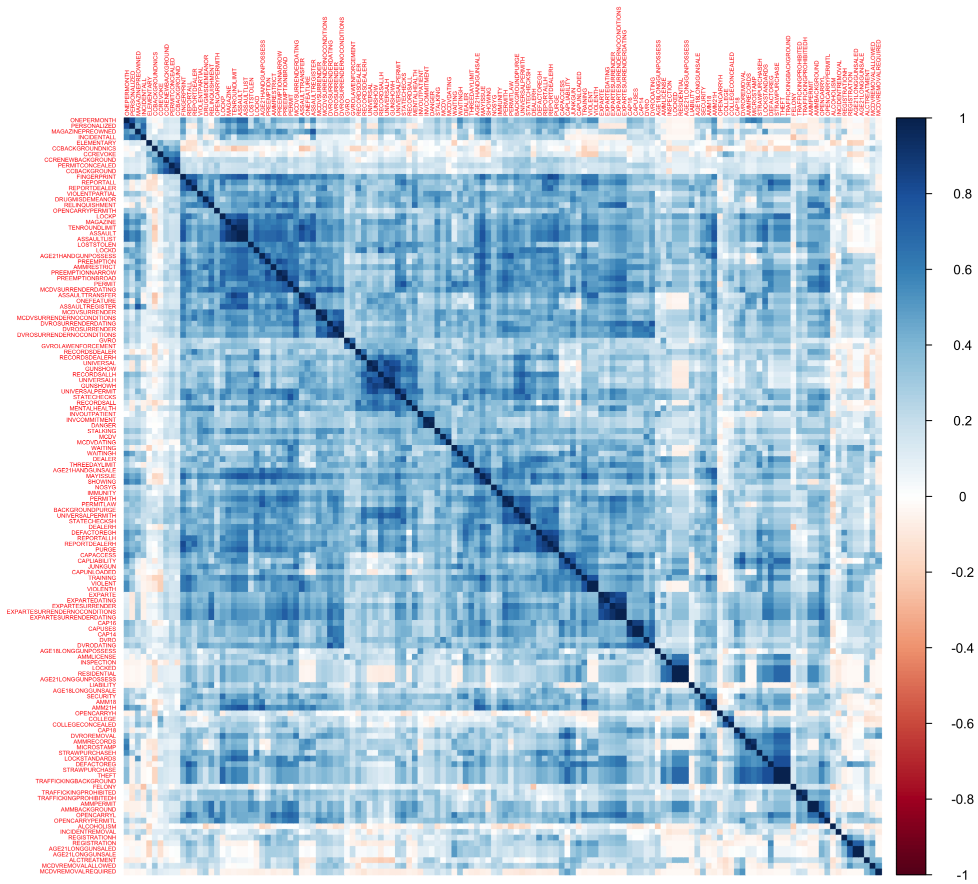


Figure 1: The correlation matrix for the law data filter for years after 2014, reshuffled to cluster laws

Hopefully this image gives incited to how complicated the structure of this data is, it is not so clear how to compress all of this information down to one variable.

Due to these above issues, it is problematic to consider these variables is a raw, unprocessed form. A method to circumvent this would be to embed our laws (each of which is a vector in $\mathbb{R}^{137}$) to a much smaller space (say $\mathbb{R}^{10}$). This can be accomplished using principle component analysis (PCA). This technique takes in our data matrix and compresses the number of columns into a given dimension. Not only does the use of PCA help with compression but it also provides a rich interpretation of our compression through analyzing the eigenvectors of our PCA decomposition. As an example we can average the laws for each state over the years 1991-2019. We find the first 2 eigenvectors of our data (the linear combinations of our variables which explain the maximal variance). We then can average over each 5 year period in our data and project onto these two vectors. Each state is given a color to help the eye better track the progress each state has made. These plots are shown below:

Figure 2: The projection of each 5 year average laws on the first two principal vectors, here the x-axis is the projection onto the first princial vector and the y-axis is the pojection onto the second principal vector. Colors are unique designated to each state.

First we can note the similarities in each image. First we see a large cluster of states near the origin which indicates that they are essentially perpendicular to the first two eigenvectors. Meaning that among the projections of maximal variance they are relatively equal. It is worth taking note this fact as it will be important for modelling later.

We then see that there is a set of more strict states. Overtime there has been a migration from the cluster with a small number of gun laws (this is essentially PC 1) to a more diverse set of gun laws. A good example of this is New York which has slowly gone from within the bulk states near the origin to one of the more strict states. Representing how it has evolved its gun control laws over time.

Based on the second eigenvector, we see diverging approaches for a more strict control on guns. The positive path is taken by states like Massachusetts, Hawaii and California. The negative path taken by states like New Jersey, New York, Connecticut. Either way we see there has been an increase in heterogeneity of gun legislation with time. Ever slowly we see that these more strict states distance themselves from the origin.

If we zoom in further to the cluster near the origin we get a different story:

Figure 3: Zoomed in version of figure 2

Under this new lens we can see some further interesting dynamics. First we notice that the migration towards the more "liberal" states can be seen on a much smaller scale with states like Pennsylvania and Delaware.

The pattern of heterogeneity still continues for the negative side of the first principle component. State which has alot of homogeneity in the 90s have slowly distances themselves from each other with time. This can be interpreted as states slowly evolving their gun control over time to fit the exact needs of the state. We will see later that it is non-trivial to make conclusive statements about the best gun control laws since each state requires a differing approach. The evolution of the principal components shows this pretty well.

As for the specific values of the first 7 principal component vectors, please see the appendix below.

Visualizing Gun Trafficking Accross State Lines

Now that we have a methods to compress our laws into a smaller dimension we can start to build intuition of the types of variables we want to include with our model as well as how our problems can be seen through the lens of the principle vectors.

In order to provide a clean visualization we will sum over each year from 2014 to 2019, grouped by the source and target state. To get a glimpse of how the gun traces changed from state to state we plot an un-normalized version of these traces.

Figure 4: Plotting each of the traces as an arrow from the scource state to the target state. We have the color of the line correspond to the target state, the linewidth refers to the number of guns traced from 2014 to 2019, the alpha level is an exponential weighting for ease of visualization.

When viewing this plot (and subsequent maps), look at the center of a state to see its color and then you can trace this color to other states to see where a majority of its out of states guns come from. For example we see that California sources many of its out of state guns from Arizona, similarly for Illinois (due to Chicago) and Indiana.

Unfortunately, there is a worrying confounder with how we view the gun trafficking. Notice that all of the states which have many guns transported to them are simply some of the most populous states. Thus, we must keep in mind some measure of size or gun demand for each state when we begin modelling. Lets try a normalization scheme to try to show where there might be "surprising" gun traffic.

First we will utilize the following normalization. We can view our tracing data as a matrix M of which the i-th, j-th entry is the guns following from state i to state j, by convention we will set the diagonal to be 0 as we want to represent guns crossing state lines. We can interpret the "gun demand" as simply the number of total firearms which entered the state. Meaning we define an new matrix N as from our old trace matrix M as:

$$N_{i,j} = \frac{M_{i,j}}{\sum_i M_{i,j}}$$

We can now plot the traces of this new normalized matrix to see if our understanding of the picture has changed. We also will remove any traces which represent less than 1% of the guns found in the source state traced from out of state.

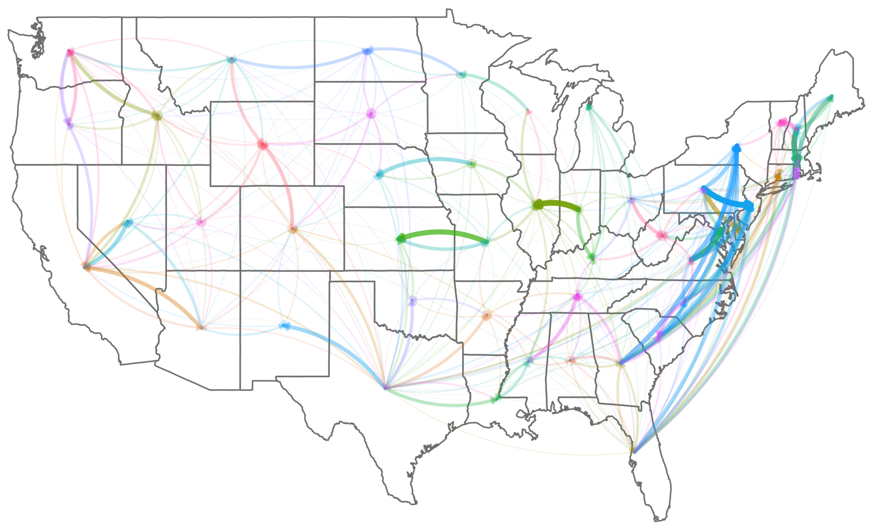


Figure 5: Plotting the trace now under a new normalization based on the number of incomming guns, filtered by providing one percent of traffic.

This starts to tell a slightly different story, now we can see that our observation from California is notable but not exceptional. We now find out some more interesting trends. First it seems like a large proportion of out of state weapons in New York are from a handful of states along the east coast. We still see that the trafficking from Indiana to Illinois is exceptionally concerning. We also see alot of these traces over long distances seem to vanish, meaning they were an artifact of the un-normalized map.

Of course we still have our results biased by states which produce alot of guns, taking this normalization to its logical conclusion we can consider a bi-stochastic normalization or our matrix using Sinkhorn's algorithm. For this algorithm we repeatedly iterate on our matrix with initialization M^0 as

$$X_{i,j}^t = \frac{M_{ij}^t}{\sum_i M_{ij}^t} \quad M_{ij}^{t+1} = \frac{X_{ij}^t}{\sum_j X_{ij}^t}$$

Under this Sinkhorn normalization we can now interpret the output of our iteration as a bi-markovian matrix where the i-th and j-th element of this matrix represents

$$P(\text{Gun manufactured in state } i \text{ goes to state } j)$$

and

$$P(\text{Gun found in state } j \text{ is traced back to state } i)$$

Under this Sinkhorn normalization we can now start to see which traces we would consider "exceptional" given our knowledge of the total number of guns leaving the state and entering the state. We again plot each trace which is of value .01 or greater and see if any new patterns emerge.

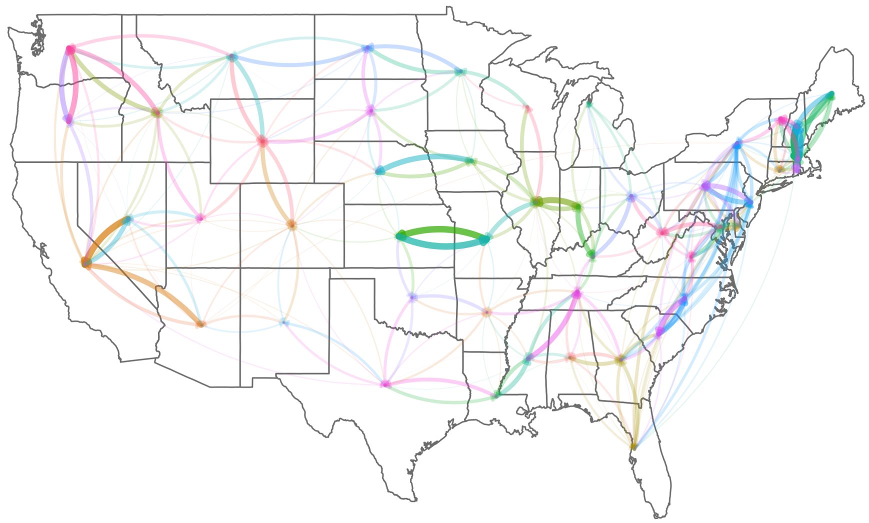


Figure 6: Plotting the trace under the Sinkhorn normalization, filtered by providing 1 percent of traffic.

First we have some observations about new connections which are emphasized here which are different from previous images. We see that the it is actually Nevada not Arizona that provides a larger proportion of weapons given their number of gun which exited the state. We see that based on the number of guns produced by Indiana that its connection to Illinois is actually of similar magnitude to Kentucky. We also see a exceptional among of gun trafficking between the states of Missouri and Kansas. Perhaps explaining (which we will see later) St. Louis county has one of the most concentrated gun violence rates in the nation.

Also worth noting about this choice of normalization is that this matrix seems to best respect geographical distance much more than our previous images. Many of these connections are related back to sharing a boarder or being of relatively close distances. Clearly geographical distance has a serious role to play in determining the number of traces from state to state. Thus, summing up what we should include in our model based off our visualizations.

When controlling for the size / demand of a state:

- The size of the states and demand for guns are important considerations in building our model
- Location is also important, closer states are likely to have more guns going from one state to another

Now that we have an understanding of how gun-traffic should typically flow from state to state. Lets try to understand how laws may influence the gun-traffic. We present the traces from our Sinkhorn normalization projected onto the principal vectors. Given a target and source state we can define the difference in their laws as

$$L_d^{s,t} = L_{target} - L_{source}$$

Where this vector L_{diff} is 1 if a law was present in the target state but not in the source, 0 if the laws are the same in both state and -1 if the law is present in the source but not in the target. We then can consider the projection of this difference onto one of the principal vectors v_i as

$$\text{Proj}_L = \frac{L^T v_i}{||v_i||^2}$$

We then plot the traces which are in the top 10% with respect to the source and target state in terms of absolute value for each principal vector. This will help show which projections are reasonable large without overcrowding these plots. Our goal is to gain intuition on what each principal vector sees in our data, what differences in laws will each PC represent and what significant traces are highly correlated with this difference in laws. We also color the trace red if it has a positive projection (i.e. the target state has the positive laws and source state has the negative laws, based on the principal vector) and blue if it has a negative projection (vice versa).

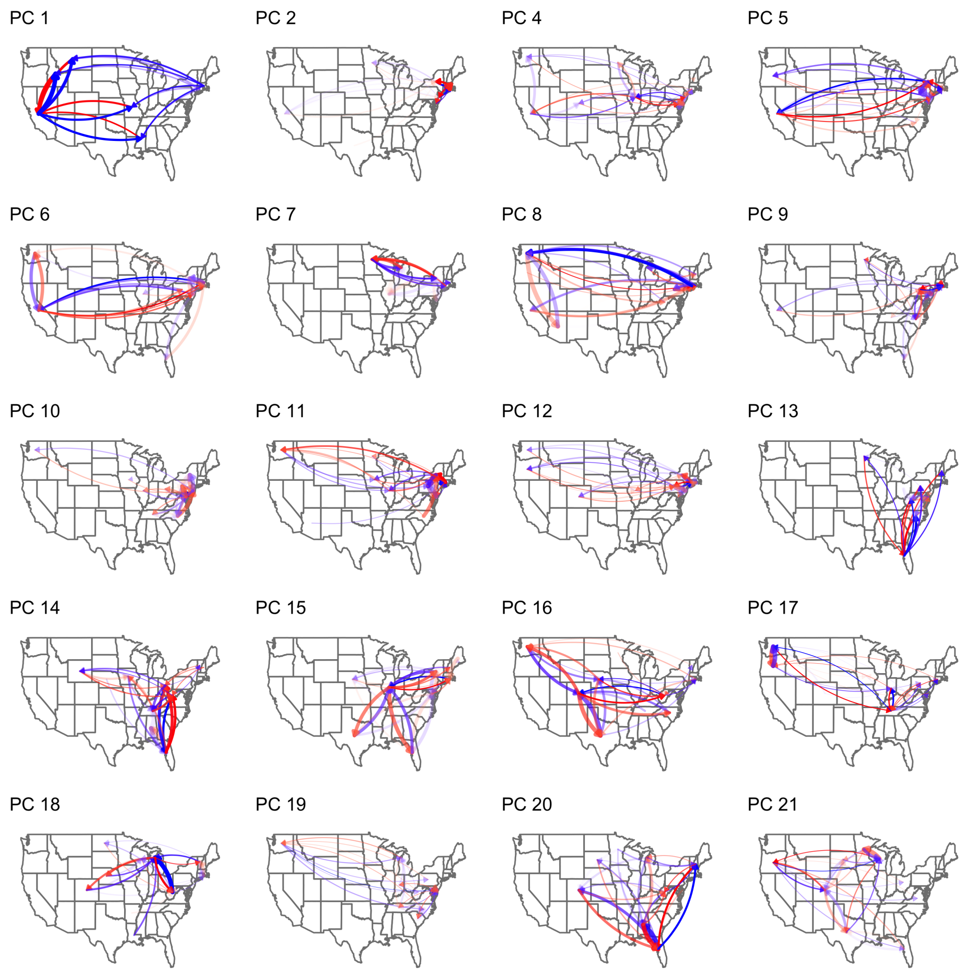


Figure 7: Projecting each trace into the first 20 principal component vectors. Note that we do not show the plot for vector 3 since it is highly correlated with Hawaii and Alaska and would show a blank continental US. Red means a positive sign connection and blue negative. We also have the transparency be the magnitude of the projection and the line width be the number of traces. We filter only traces which are in the top ten percent for both their target and source state in terms of projections

We can now begin to make some comments on how differing principal vectors “see” the differences in gun legislation. I will make some cursory comments here but I really encourage taking some time to look at this image, the principal vectors represent rich structures and alot can be gained by understanding how they impact your data. We see that many of these projections have their largest magnitude between specific clusters of states, under this interpretation we can think of these principal vectors as representing a weighted interpolations between different states laws.

Visualizing Gun Violence Incidents Versus Social and Legal Factors

Now we turn our attention to the second problem we address, trying to under stand the occurrence of gun violence incidents and their relation to laws. For the remainder of this project we define the number of people incident to be the total number of people who are either killed or injured in the event of gun violence. Our goal will be to understand what laws are present or not present when a large number of people are incident. Whenever you see the word incident think killed plus injured.

For this section we will mainly focus on summarizing the data at a spatial level alongside the relation with social factors. We also present a projection of the state legislatures onto our principle components of our laws.

First we should get a good sense of our data by plotting some simple relations. Lets analyze the gun violence data temporally. For this set of plots we will try to analyze the sequence I_d where d is a date in the time span of Jan 1, 2014 to the time of pulling our data. I_d is the number of people incident to gun violence (meaning we add together the number of people killed and injured). First we can simply plot the evolution over time.

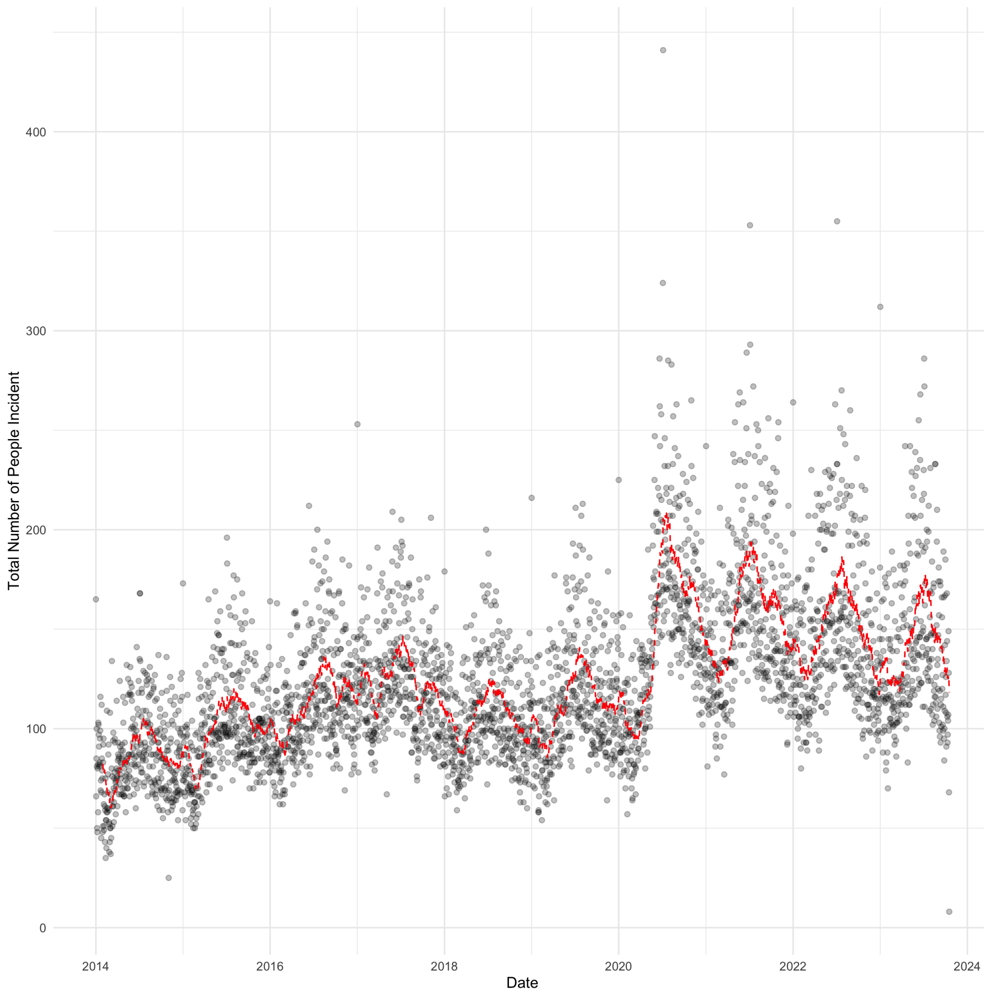


Figure 8: The number of people incident to gun violence per day. Red dotted line is 30 day moving average. Draw your attention to the y-axis and contemplate how you feel.

First we can discuss what is unexpected here, there seems to be a jump from observations half-way through 2020 where there are far more people incident to gun violence. This is interesting as you would expect the opposite trend. Since lock-downs due to Covid-19 were common you would expect less people to be exposed to gun violence. Perhaps there is another reason for this sudden jump (and perhaps the overall increase of incident as a whole).

Fortunately the GVA insures that most data-points (A gun-violence event) have a corresponding incident report. Lets filter through to see if perhaps more crimes of a certain type were reported before vs after 2020. To achieve this we will look at the common words used in these incidents reports pre-2020 and post 2020. Hopefully there will be some difference which can explain this jump.

To accomplish this we plot two word clouds to compare what vocabulary was used before and after 2020. We look through each report associated with a gun violence incident and then count the number of non-stop words. We also remove words which were structural components of the report so to only get the relevant vocabulary.

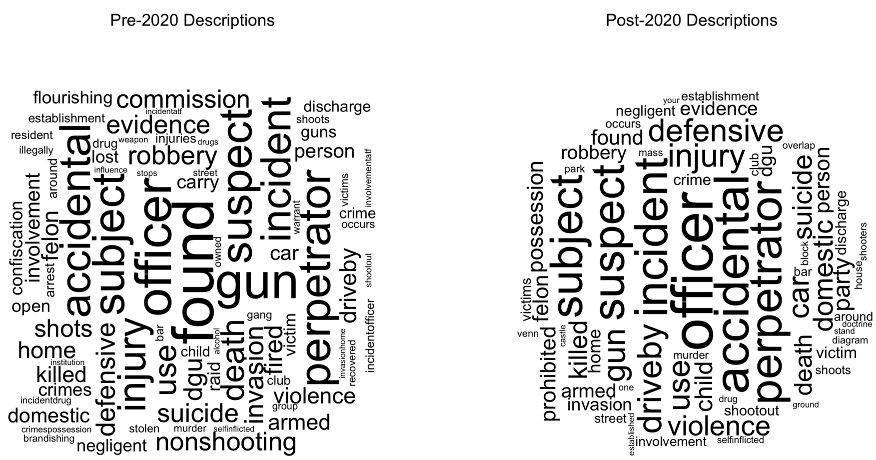


Figure 9: The most common non-stop words for reports before the year 2020, filtered to remove strucuture words. Size refers to commanality.

Interestingly you can see a drift in the frequency and diversity of wording in these incident characteristics. My[1] currently held belief is that after 2020 the GVA streamlined their data-entry system (perhaps automated parts of it). This would explain how there is a larger number of reports with a less diverse vocabulary. Unfortunately I could not find any exact reason for this in the data so this is the best explanation I have. We will leave this question here and continue on.

Besides this jump, clearly there is a clear periodicity to our data. It would be helpful to understand the impact that the time of the year has on the number of people incident. It would allow hospitals and local government to prep for the worst month in terms of violence and on a whole we can understand the actions which lead to gun violence better. We strip out the average monthly and weekly effect to analyze our data. In order to avoid issues with the jump we discussed we will do this stripping for only the years 2021 and later. Notice this technique could be applied to the whole data set by removing the average year impact (or even just a pre-2020 and post-2020 impact).

[1] Allow me to be personal for a moment

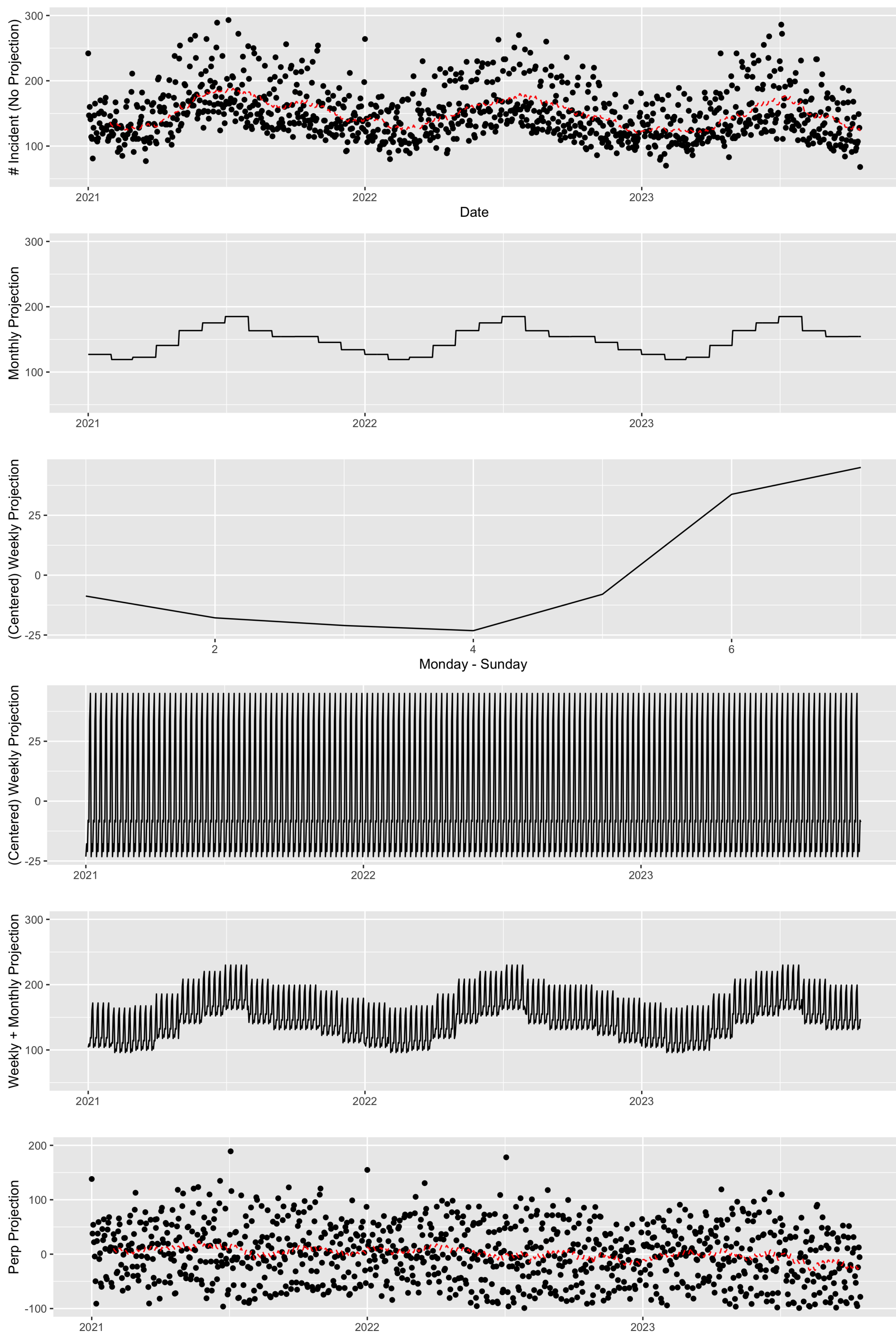


Figure 10: From Top to Bottom: 1). Figure 10 restruicted to be after 2020. 2). The projection of the first figure to months. 3). The projection on the residual (first figure minus second figure) onto days of the week. 4). The 3rd figure in reference to 2021-2023 time. 5). Adding the second and fourth figure. 5). The residuals.

Once we remove these two temporal components then we see that the average stays consistently around 0.

Meaning that we are only left with the average day to day variation for the year. Barring the occasional holiday or specific event we expect that month and day of the week are the two important temporal variables here. Also, notice that there is a slight squeeze at the beginning/end of the year so there is a slight amount of heteroskedasicity in this sequence but nothing too concerning.[2]

Since the laws only change year over year in our data, we can ignore temporal variables going froward, but in general they are helpful to know.

Now we can investigate the spatial relationship and some notable areas in the US with a high gun-violence rate. As a first step lets plot all of the incidents which involves at least 2 people incident. We plot their location as well as varying the size and transparency of the point to show the number of people incident to that specific gun violence event. We also label the 10 worst gun violence incidents in the data (From years 2014 - October 2023, note that the Vegas shooting is missing due to a data entry issue and this data was pulled before the Lewiston Maine shooting). The colors are help to differentiate between states.

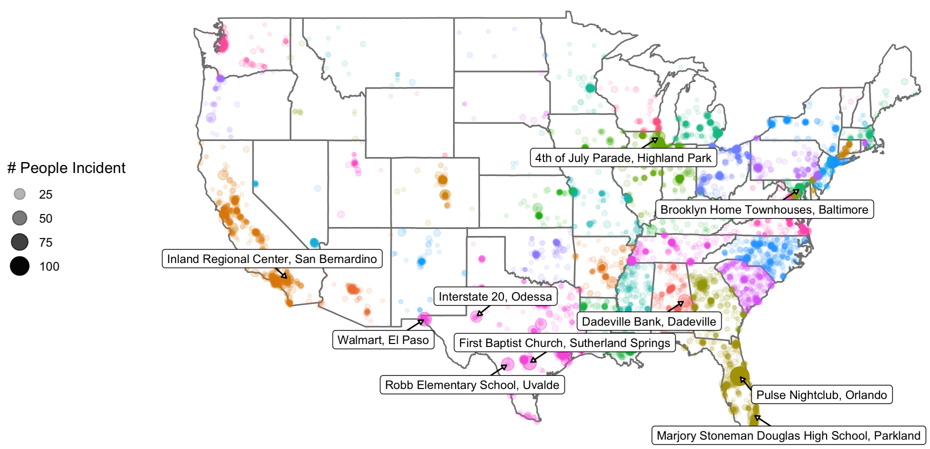


Figure 11: Gun Violence in the Continential US, size and alpha represent number of people incident, color is for visability. The 10 largest gun violence events in terms of inicient labelled.

Now that we have seen the data at the point level, we can begin to aggregate upwards, starting from the county level and then moving to the state level. Our goal is to highlight which areas are include the most gun-violence while incorporating normalization when illustrative. First we can look at the number of people incident to gun violence in each County. Here our color refers to the number of people incident normalized by the by population of the county on the log scale. This should give an ad-hoc idea of what areas would be considered dangerous. We also now include Alaska and Hawaii.

Lets look at the counties with the most people incident to gun violence. Here we plot each county in the US along with color here referring to the number of people incident over the years 2014-2019. We also label the top 10 counties in terms of this metric.

[2]Also, as Brian pointed out it seems like the outliers here are New Years and July 4th

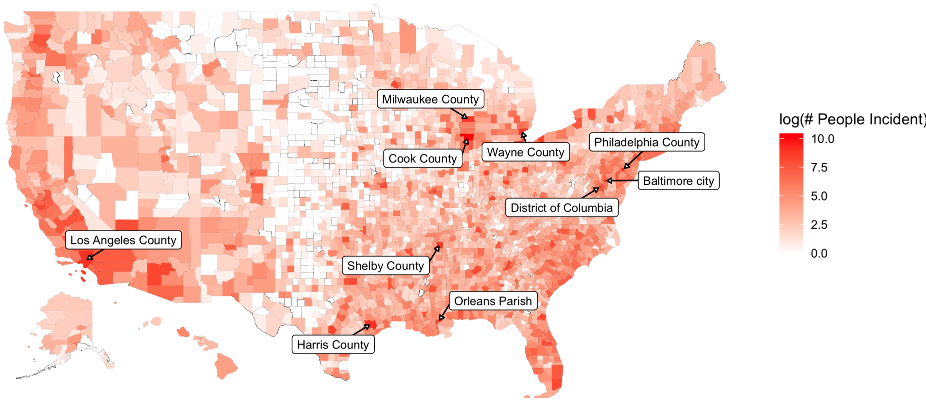


Figure 12: Shootings in the Continential US (county level), color refers to log(People incident). We squish any tract with a value larger than 5. Labels for 10 counties with most people incident.

This plot shows an un-normalized value so we expect that large cities (like LA county) would have the most people incident to gun violence. However this is a common misnomer since a more accurate measure would be to have the number of people incident per person. We illustrate this difference using a cartogram. Now we have the US counties inflated or deflated due to their per population number of people incident. We also label the 10 counties with the largest number of people incident per person.

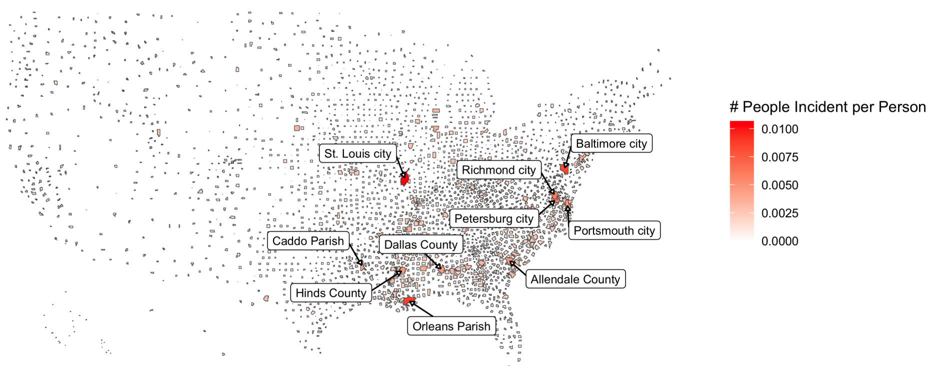


Figure 13: Cartogram of gun violence in the Continential US (county level), color and in(de)flation refers to People incident / Population.

And as one final step we can also view this same metric at the state level as well.

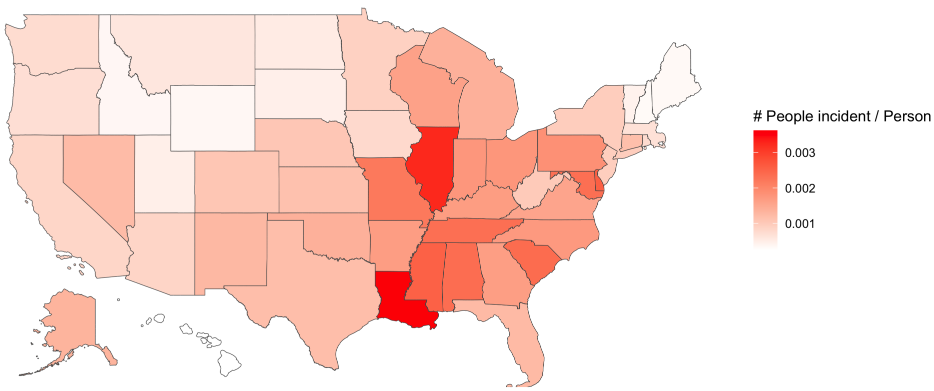


Figure 14: Gun violence in the US (state level), color refers to People incident / Population

Now that we under stand the issues of gun violence at each spatial hierarchical level we can also begin to understand to what extend the principle vectors will be able to see our states. We take each principal vector and project each state legislature onto these principle components. Similar to the image with the projection of the traces. We can think of each principle vector representing a ’’legislature” which we will promote laws (positive value in the vector) or demote laws (negative value). We plot the first 20 PC and see which states they are hot on.

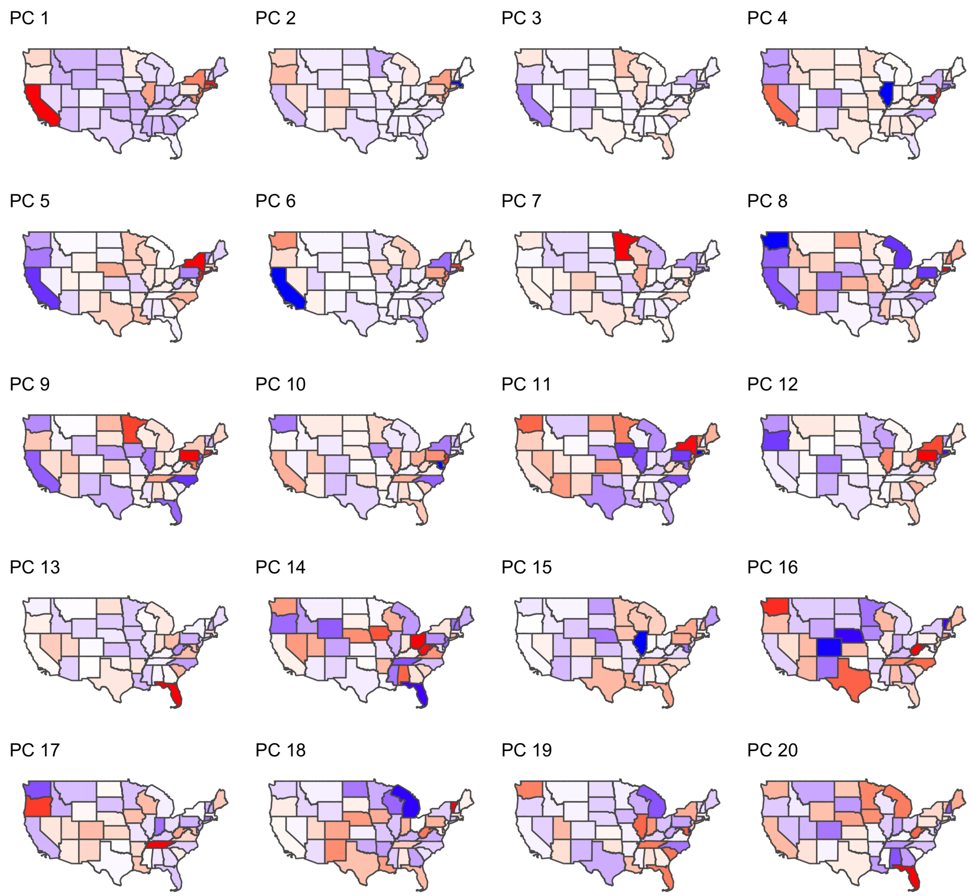


Figure 15: Projection of State Legislature on the first 20 principal vectors. Note PC3 is heavily focused on Hawaii / Alaska. Red refers to a large positive projection while blue refers to a large negative projection.

As expected the principal vectors distinctly focus on different states, in fact they provide a very helpful measurement to show what states have similar legal structure. States which match colors for a majority of these PCA figures are those which have similar laws. Try to see you favorite states' color for the first few PC's and see which states share its coloring.

Finally we can analyze our social variables to see if we would believe that they have an impact on the number of people incident to gun violence. First we show the correlation between the variables we drew from the ACS database.

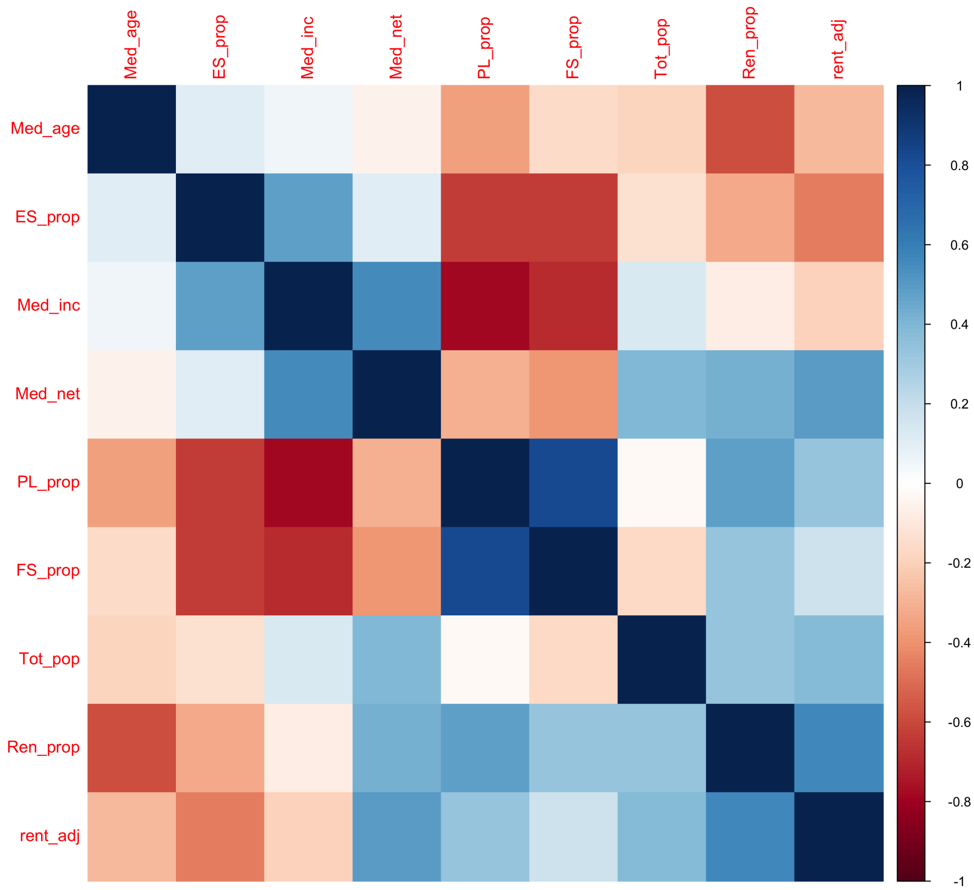


Figure 16: Correlation between our Social variables drawn from the ACS survey, shuffled to cluster correlations.

Nothing two surprising here. Next we also look at a 1 dimensional binning of each of these variables compared to the average number of people incident in a gun violence event. Each bin captures exactly one 20th of the population in our data-set. Here we have the y-axis represent the mean number of people incident and the x-axis details which bin of our social variables we are in.

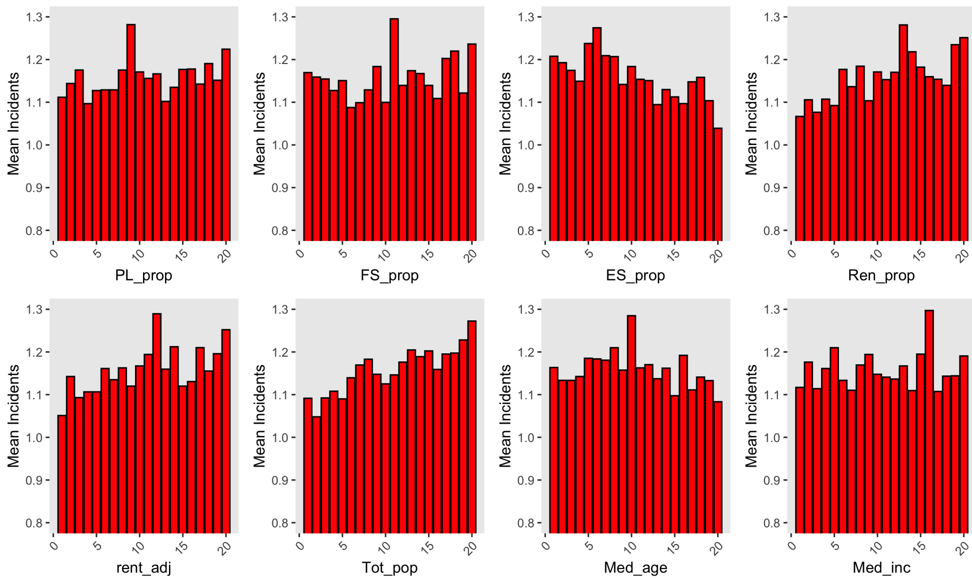


Figure 17: Mean number of incidents when projected on to one 20th of the population according to a metric from our ACS social variable, x-axis represents bin number.

Summing up the single dimensional relationships, we expect the number of people incident to a gun violence incident to be higher when:

- The poverty level increases (small effect)
- The number of people on food stamps increases (small effect)
- The employment level decreases
- The proportion of people renting increases
- Rent (in relation to income) increases
- The total population of your area increases
- Median Age seems to have little effect
- Income Seems to have little effect

These variables by themselves may not be the most helpful but they will be vital to aid in controlling for external variables in our gun model. Speaking of which, we turn to now.

Modeling/Analysis

For both of our problems we attempted a poisson GLM model with Lasso normalization, this was done for two major reasons.

1). We are dealing with count data and the poissonian model is a canonical choice to handle this.

2). We eventually want to "rank" laws from most to least effective in causing gun violence and gun trafficking. Lasso will help with model selection.

Overall both models fit in the following paradigm. We design a specific penalty based on the L1 norm of **only the legal variables** this allows the penalty parameter λ to start at a null model based on control variables (when λ is high) and slowly bring in the most important features as we lower its value. Not for the remainder of this section we describe null variables to be those with no lasso penalty and alternate variables to be those with a shrinkage penalty.

The assumptions for poisson regression are:

- The log of the response and our variables have a linear relationship

- Our rate changes in a multiplicative manner
- For each response level the mean and variance are equal
- The Errors are iid distributed

To be honest due to the complexity of our data these are hard to verify. Certainly it feels that the rates being multiplicative makes sense, and since we have count data then we are constrained to a negative binomial or poisson. I choice the poisson since it minimized cross validated mse (this comparison was not included in the report for brevity). I am inclined to believe there is over-dispersion in the data-set since the overall mean is not equal to the overall variance[3]. Even though this does not directly imply over dispersion, their is so much intrinsic variance in this data that is not captured by our variables that I do think it would be a problem if giving confidence intervals. I avoiding reporting these for the above reason. Unfortunately my model choice is limited due to not wanting to code up a new algorithm, so here we are.

Ultimately, the generation of gun violence, in theory, should follow a poissonian process but signs point to a more complicated story. We assume that this model is a good fit and move on to our analysis.

We present two models for our trafficking question,

Goal: Recall that our goal is to predict the number of guns recovered in state A which are sourced to state B, this is meant as an analog to the number of guns trafficked from state B to state A. We denote state A as the target and state B as the source, we describe the number of guns from B to A as the flow. For both of these models we remove observations with 0 flow as their dynamics are significantly different from those with positive.

Model 1 (State Margin Blind): This model attempts to normalize the gun demand by using the log of the state population

Null Variables:

- log(Great Circle Distance) ℓ_D
- log(Source State Population) ℓ_S
- log(Target State Population) ℓ_T

Alternative Variables:

- Presence of a Law $\vec{L}$ (restricted to Laws which occurred in more than 5% of states)
- Total Law Count T

Response:

- The flow from the source to target $f_{S,T}$

Thus the functional for of this model is (with α, β, γ, I as parameters):

$$f_{S,T} = \ell_D^{\alpha_D} \cdot \ell_S^{\alpha_S} \cdot \ell_T^{\alpha_T} e^{<\beta,\vec{L}>+\gamma T+I}$$

The choice of log here is to represent our 3 null variables as a prefactor in thr front of our rate. Meaning that our legal variables will shrink or grow this normalized prefactor rate based on if they are positive or negative. Note each legal variables(except Total Law Count) is of the same marginutude so they can be directly compared.

Model 2 (State Margin Seeing): This model normalizes gun demand by seeing the margins of the problem. Meaning that the model has information on the source and target state marginalized over all flow with either value but does not see the interaction of the source and target.

Null Variables:

- log(Great Circle Distance) ℓ_D
- Source State (as factor) N_S

[3] I couldn't find a way to present these values cleanly in this report but the variance is orders of magnitude larger than the mean due to rare events in both problems

- Target State (as factor) N_T

Alternative Variables:

- Presence of a Law $\vec{L}$ (restricted to Laws which occurred in more than 5% of states)
- Total Law Count T

Response:

- The flow from the source to target $f_{S,T}$

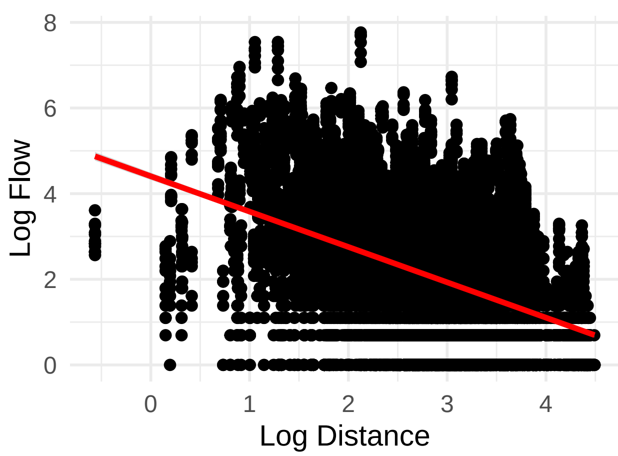
Thus the functional for of this model is (with α, β, γ, I as parameters):

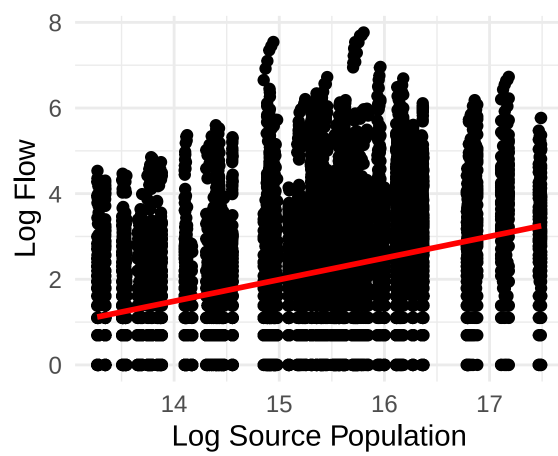
$$f_{S,T} = \ell_D^{\alpha_D} \cdot e^{<\beta,\vec{L}>+\gamma T+<alpha_S,N_s>+<\alpha_T,N_T>+I}$$

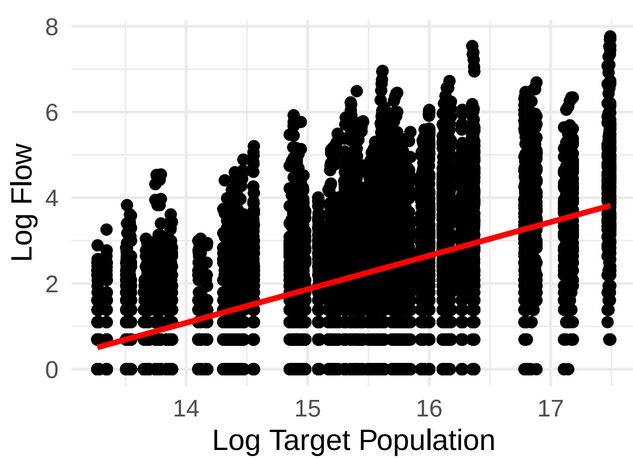
The choice for the margins on this problem to help with the normalization is to give the model the average number of guns leaving and entering the state over the course of our data. Then the coefficients of the laws really try to explain the interactions between states beyond those explainable by " This state sends/receives alot of guns".

We will compare these two models with using cross-validated poisson deviance (this was cosen over MSE due to the drastically different scales of our observations) and report the most significant laws in each model (note that this is not chosen based on poisson deviance but instead raising the value of λ until only 10 or so laws are left). Note that even if one of these models outperforms the other that they receive a wildly different variable types so both are important to keep in mind.

To illustrate the choice of transformation here are single dimensional regressions against each of our null variables:







We present one model for the gun violence question,

Goal: Here our goal is to predict the number of people incident (number killed + number injured) for each county which has at least 1 gun violence incident year over year. When we actually do our modelling we will filter our data by if they are high violence (have at least 50 people incident for a given year) or low violence (have less than 50 people incident per year). This helps provide recommendations for two different types of counties, of which their dynamics may be drastically different.

Null Variables (Each at County Level):

- log(Total Population)
- Med_age
- log(Median Income)
- Proportion in Poverty
- Proportion on Food Stamps
- Proportion Employed
- Proportion of housing for rent
- Rent as a proportion of income
- year (as factor)

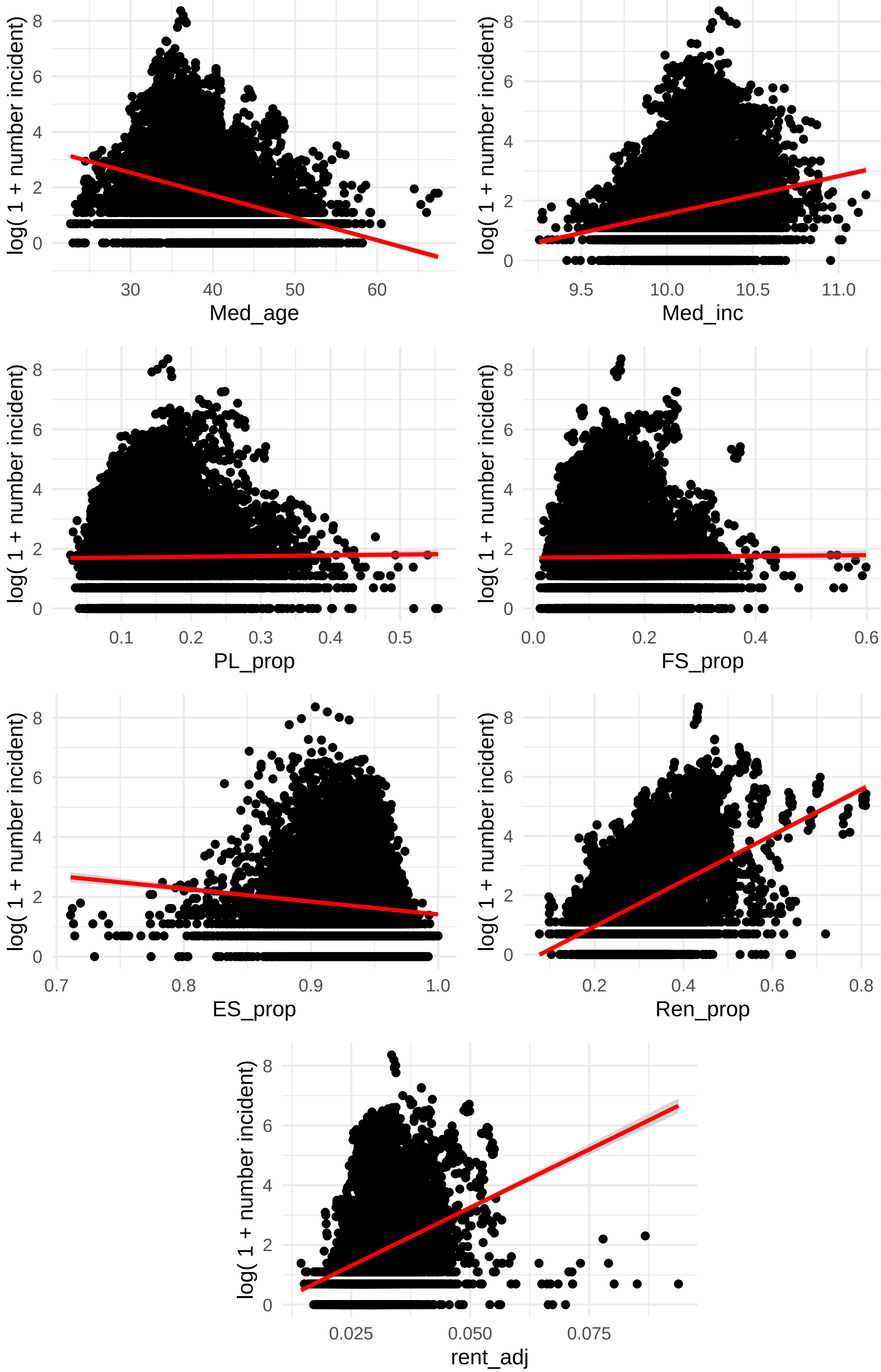
Alt Variables (At State Level):

- Presence of a Law (restricted to Laws which occurred in more than 5% of states)
- Total Law Count

Response:

- The number of people incident in that county for that year

Due to the number of variables here I will not write up the formula but the choice for log and non-log variable has to do with the size of each observation (as population and income are on the size of 10000s) and to give a good normalization to our counts. We also give the single dimensional regression between each of our variables here (Not that Med_Inc and Tot_pop are in their log forms here):


log(1 + number incident)
Med_age
Med_inc
PL_prop
FS_prop
ES_prop
Ren_prop
rent_adj
0
2
4
6
8
30
40
50
60
9.5
10.0
10.5
11.0
0.1
0.2
0.3
0.4
0.5
0.0
0.6
0.7
0.8
0.9
1.0
0.025
0.050
0.075

Visualization and interpretation of the results

In this section we will detail how our models worked in both the gun trafficking problem and the gun violence problem. Before we give our results and interpretations we will discuss at a high level what we will use Lasso for. Our goal is to try to discern which laws are the most impactful for each of our models. To do this we run lasso for each of our models. You will see the trace plot for each model as well as a cross-validating prediction error. We will then show the most impactful laws under the effective deviation metric. This metric is defined for each law with the following formula, let C_L be the coefficient for law L and P_L be its proportion in the data set:

$$ED_L = |C_L|\sqrt{P_L(1 - P_L)}$$

This metric tries to best find features which divide our space of states in approximately equal sizes while also having a large coefficient size. We will give this ordering under the choice of λ which gives about 10 laws in the lasso regression. This was made to provide an effective ranking that is short and consise.[4] Each of these lists would be a good place to start looking at more complicated dynamics. Not that these may not be the terms with the largest coefficients but those which have a long presence in the model as λ increases.

We also show the trace plots for each model as well as the cross validation errors for differing values of lambda. If we were looking to try to predict the responses for these models these plots would be particularly helpful. We put them here for completeness and to show how our chosen λ for ranking will be different than the optimal one. These plots did not help the choice of λ when reporting the most impactful laws.

The last plot you see will be a training fit plot where we see if our model has issues with differing size datapoints. We also plot a log base accuracy measurement to help better understand to what multiplicative factor we are over / under predicting.

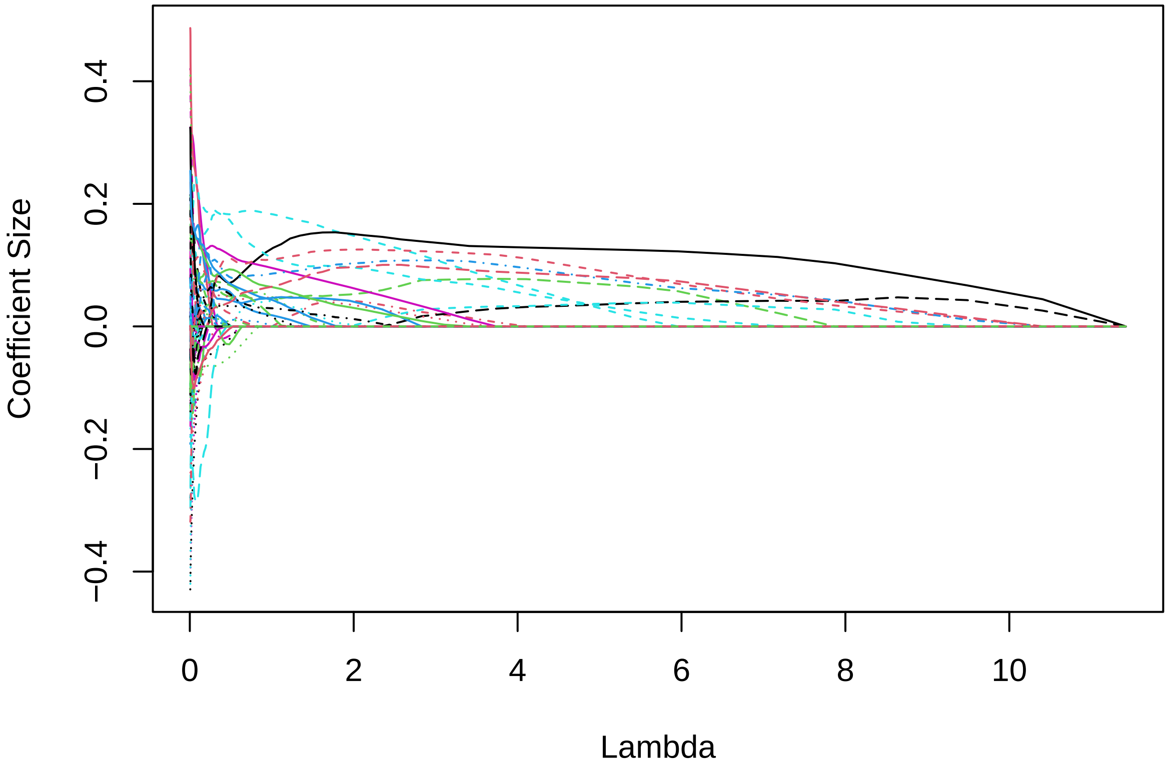
Note that depending on the gun trafficking versus violence model the coefficients have a different interpretations.

In the trafficking model if the coefficient is positive that means it increases the flow (on average) when a target state has the law which the source state does and it decrease the flow when the source state has the law that the target state does. A negative coefficient has the opposite interpretation.

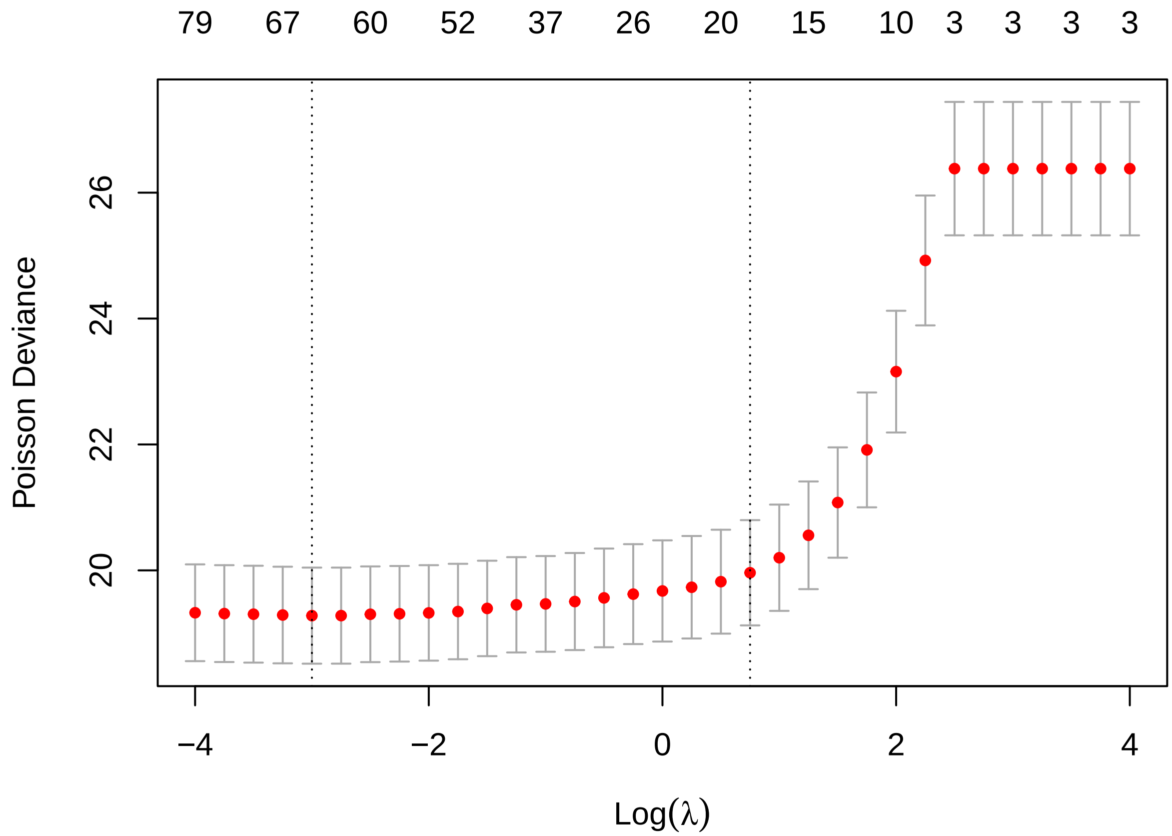
In the violence model if the coefficient is positive it means (with all other things held equal) that its presence increases the number of people incident to gun violence. If the coefficient is negative then it decrease the number of people incident.

[4] If you are interested in the ranking for other values of λ please let me know. I can send them to you

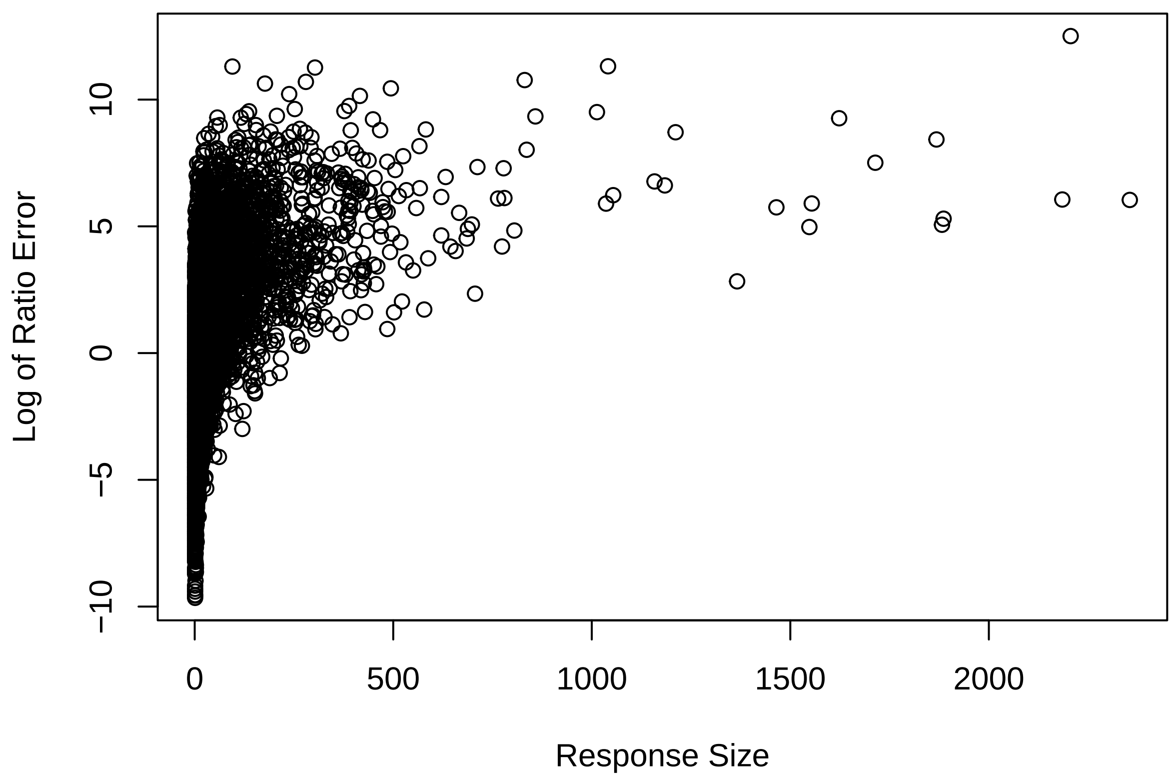
Blind Margin Model for Gun Trafficking:



Here we can immediately see that most laws will get shrunk immediately (even those which have a large coefficient in the zero shrinkage model).



Notice that we can see that immediately where all of coefficients for laws are shrunk to zeros (a little after log lambda is larger than 2). For each of these plots the first dotted line is the minimal cross validated error and the second dotted line is the larges shrinkage effect that is one standard deviation from the optimal error.

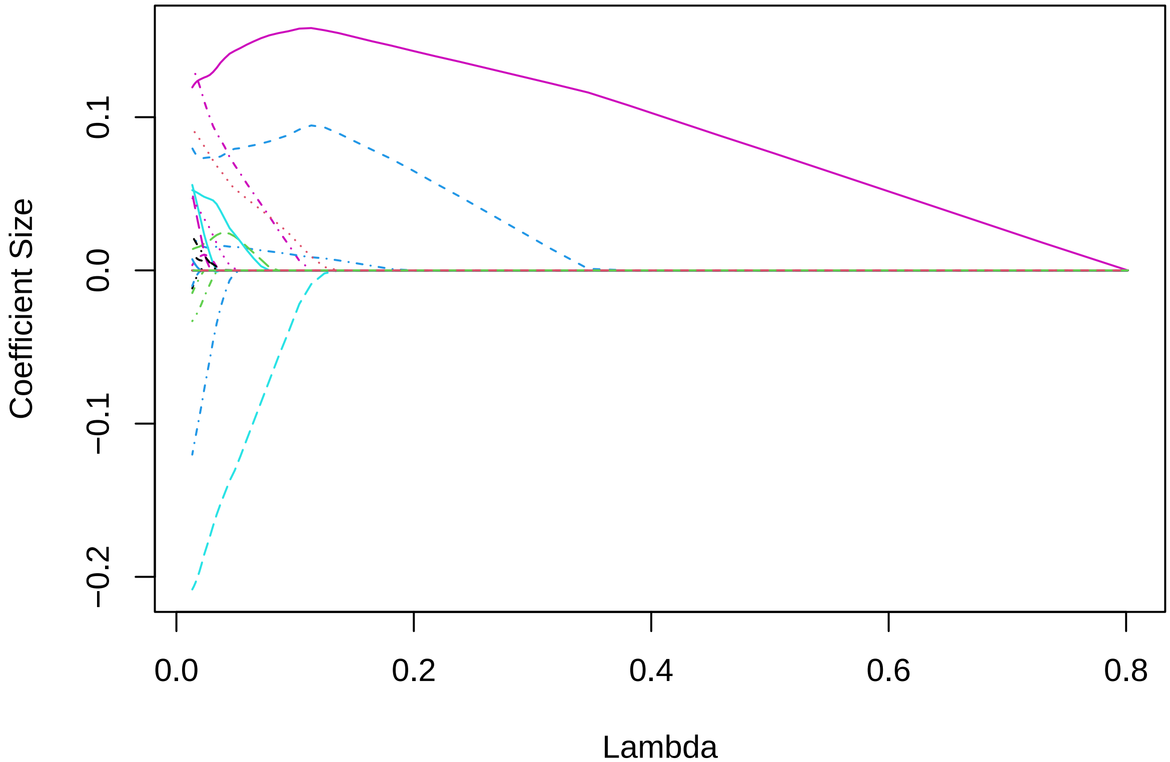


It seems like we have issues with under estimating large responses and over estimating small responses in this model.

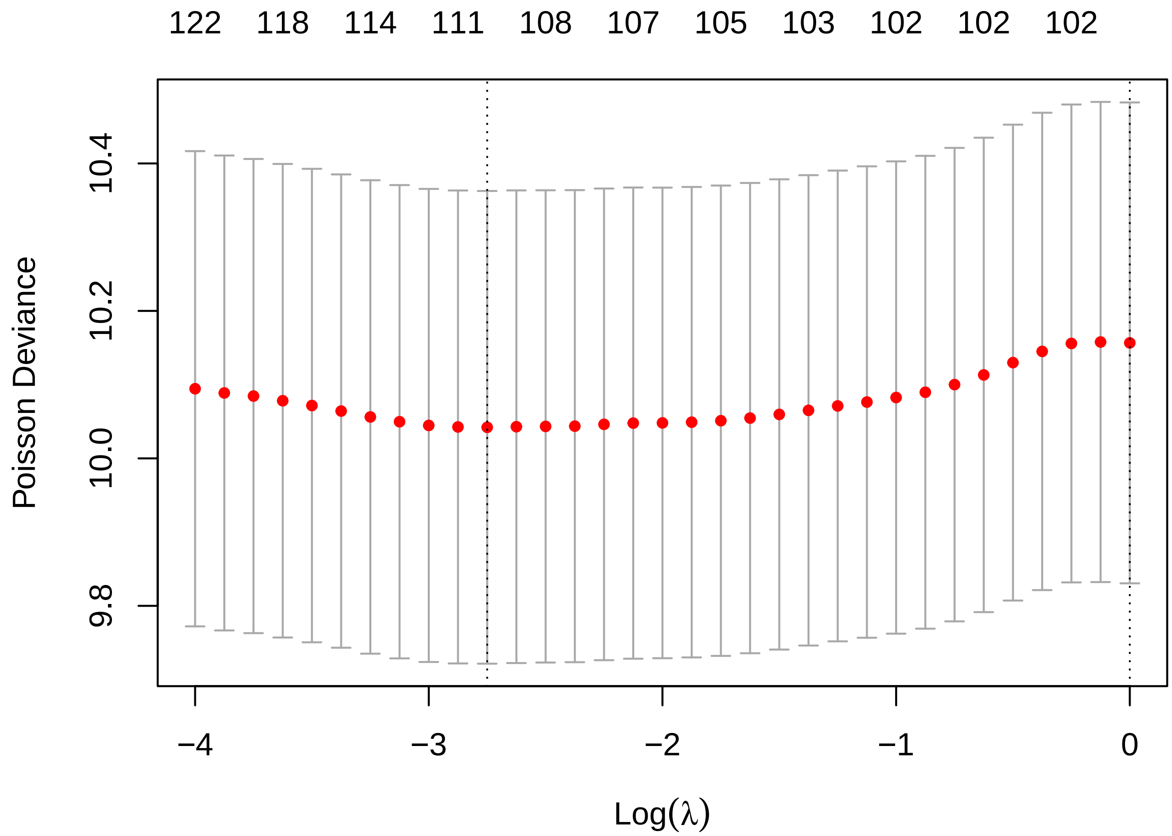
Table 7: Most Relevant Laws For Gun Trafficking (Margin Blind)
[Lambda = 4]

Law	Coefficient	Proportion Occurance	Effective Deviation
IMMUNITY	0.097	0.340	0.046
DVROSURRENDERNOCONDITIONS	0.088	0.290	0.040
JUNKGUN	0.113	0.120	0.037
RECORDSALLH	0.077	0.257	0.034
RECORDSDEALERH	0.067	0.383	0.033
ONEPERMONTH	0.129	0.060	0.031
SHOWING	0.056	0.140	0.019
BACKGROUNDPURGE	0.033	0.310	0.015
PERMITH	0.031	0.260	0.014
RECORDSALL	0.002	0.117	0.001

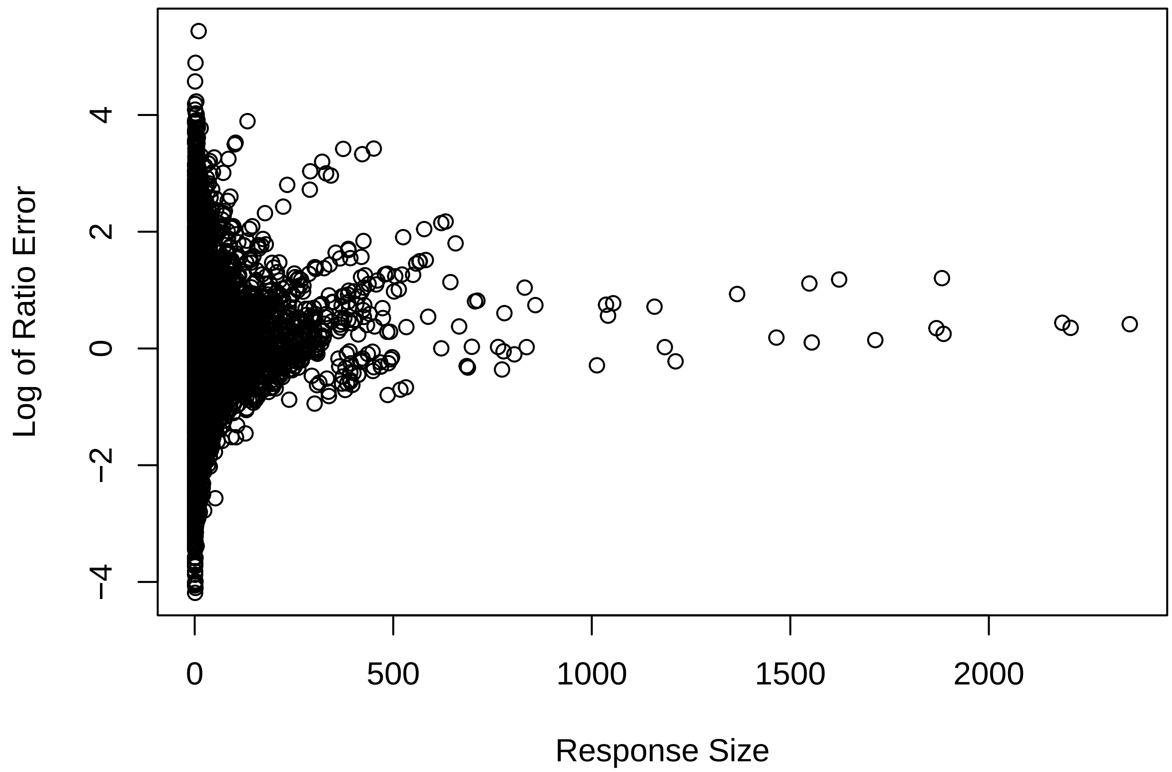
Margin Seeing Model for Gun Trafficking:



We can see that in this margin blind model the shrinkage effect is even more pronounced. Compare the values of lambda in this plot compared to above.



We can see immediately that this Margin seeing model has a much higher predictive accuracy than the margin blind. Weather this gain in accuracy is worth the extra 100 variables for each factor of source and target state is up to the reader. Notice also that there is not much of a change when shrinking all laws to 0.



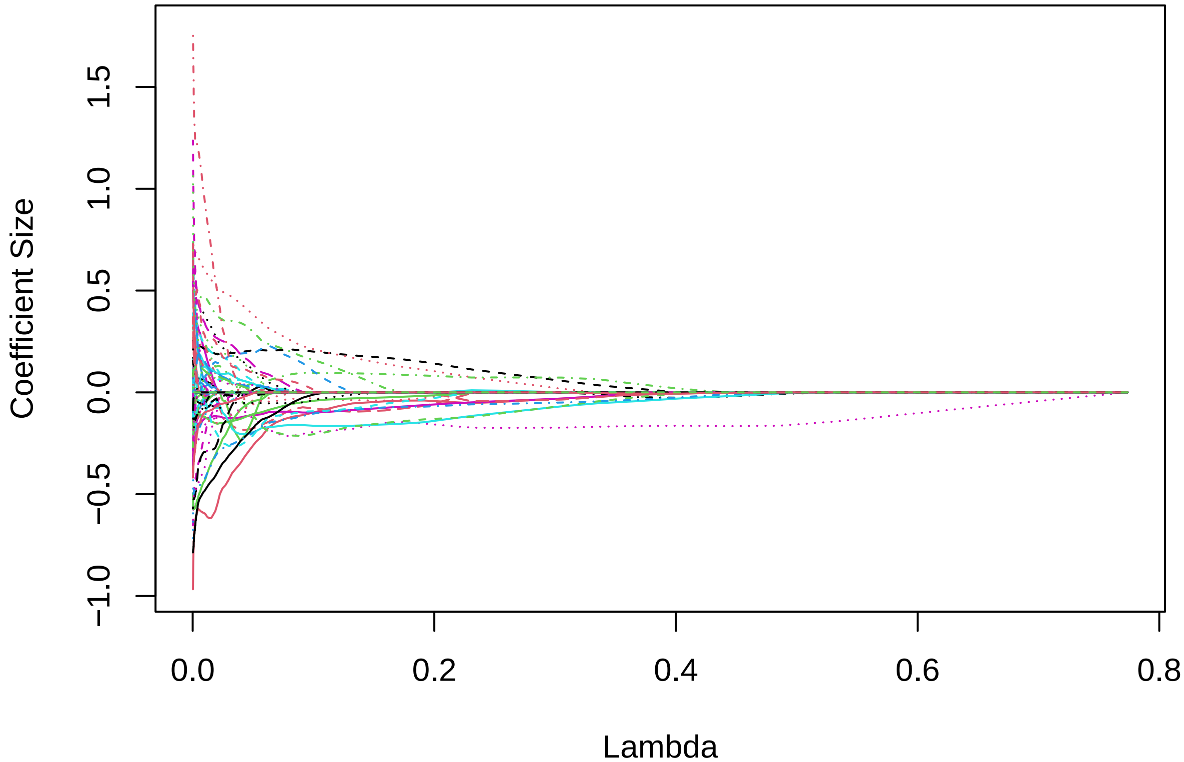
It seems like the odd training fit from before has been resolved.

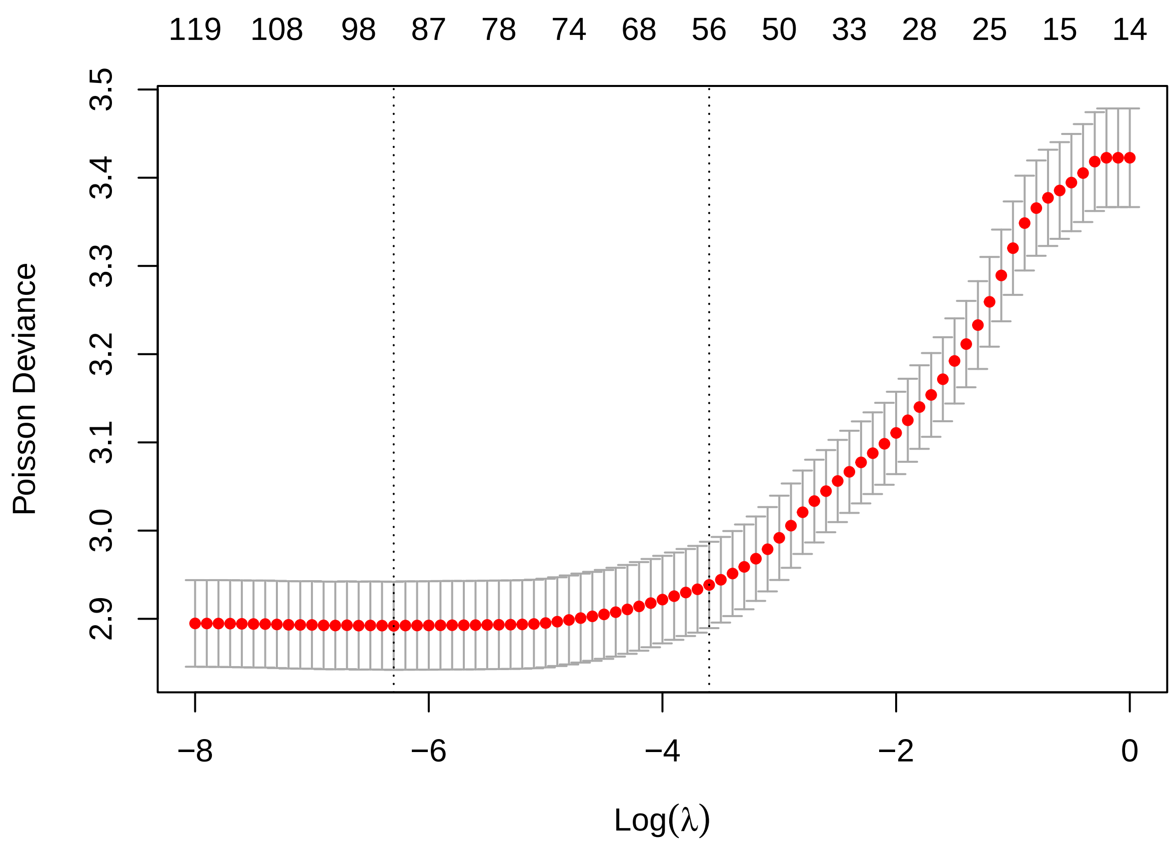
Table 8: Most Relevant Laws For Gun Trafficking (Margin Seeing) [Lambda = .05]

Law	Coefficient	Proportion Occurance	Effective Deviation
GVRO	0.144	0.063	0.035
PERMIT	0.068	0.137	0.023
LOSTSTOLEN	0.053	0.173	0.020
MICROSTAMP	-0.129	0.023	0.019
AMMLICENSE	0.079	0.047	0.017
MCDVSURRENDERNOCONDITIONS	0.023	0.213	0.009
PERMITCONCEALED	0.022	0.803	0.009
AGE21LONGGUNSALED	0.015	0.037	0.003
DANGER	-0.001	0.553	0.001

Model for Gun Violence in the US (number of people incident less than 50, low violence):

For the next two models I will let the images speak for themselves, not additional commentary is needed here.





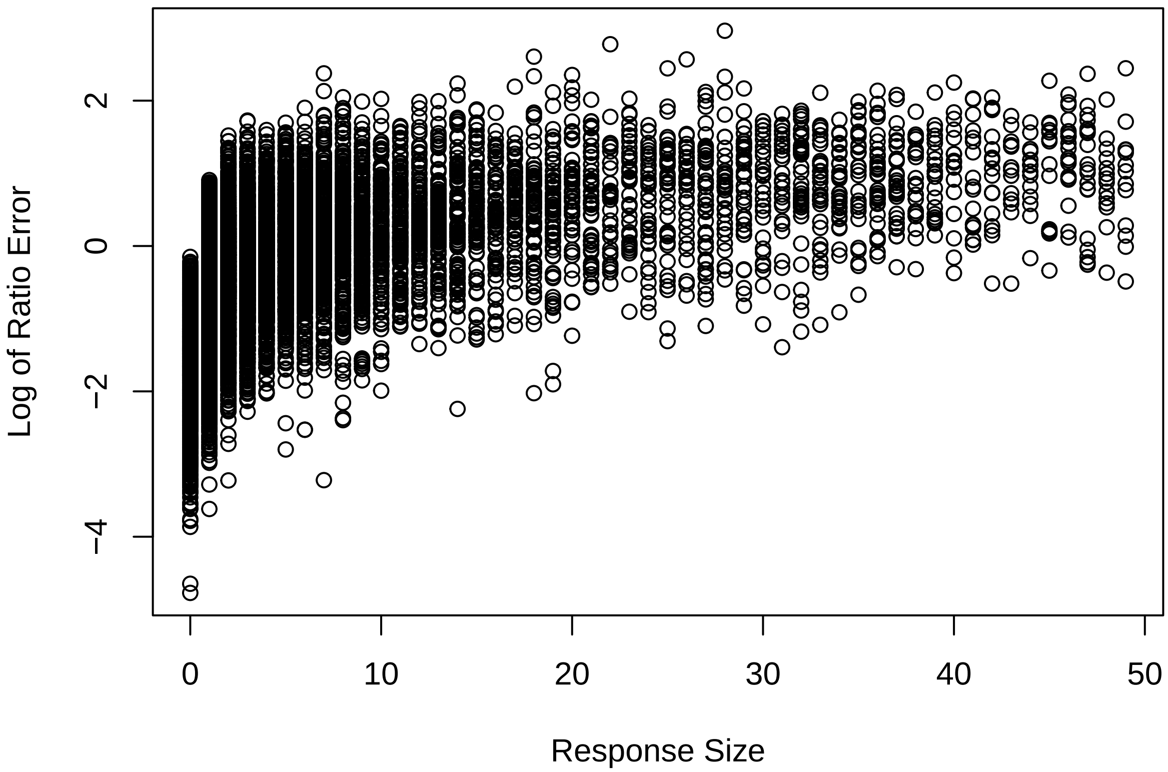
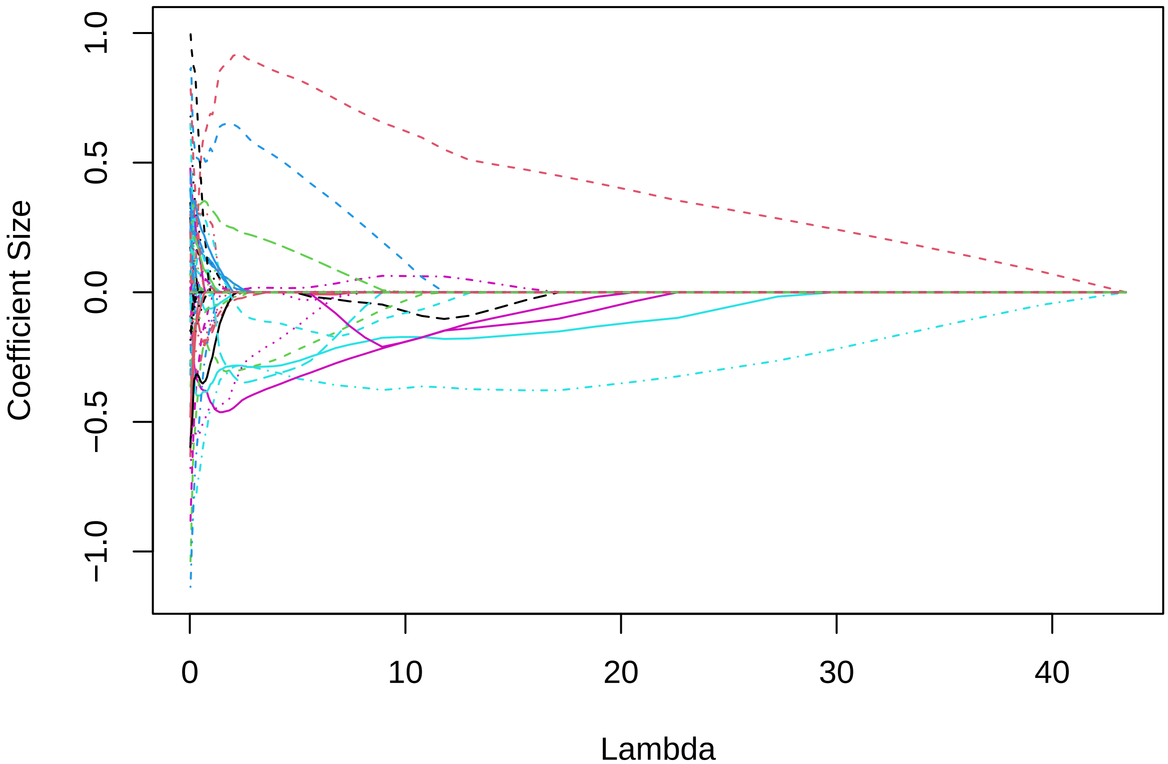
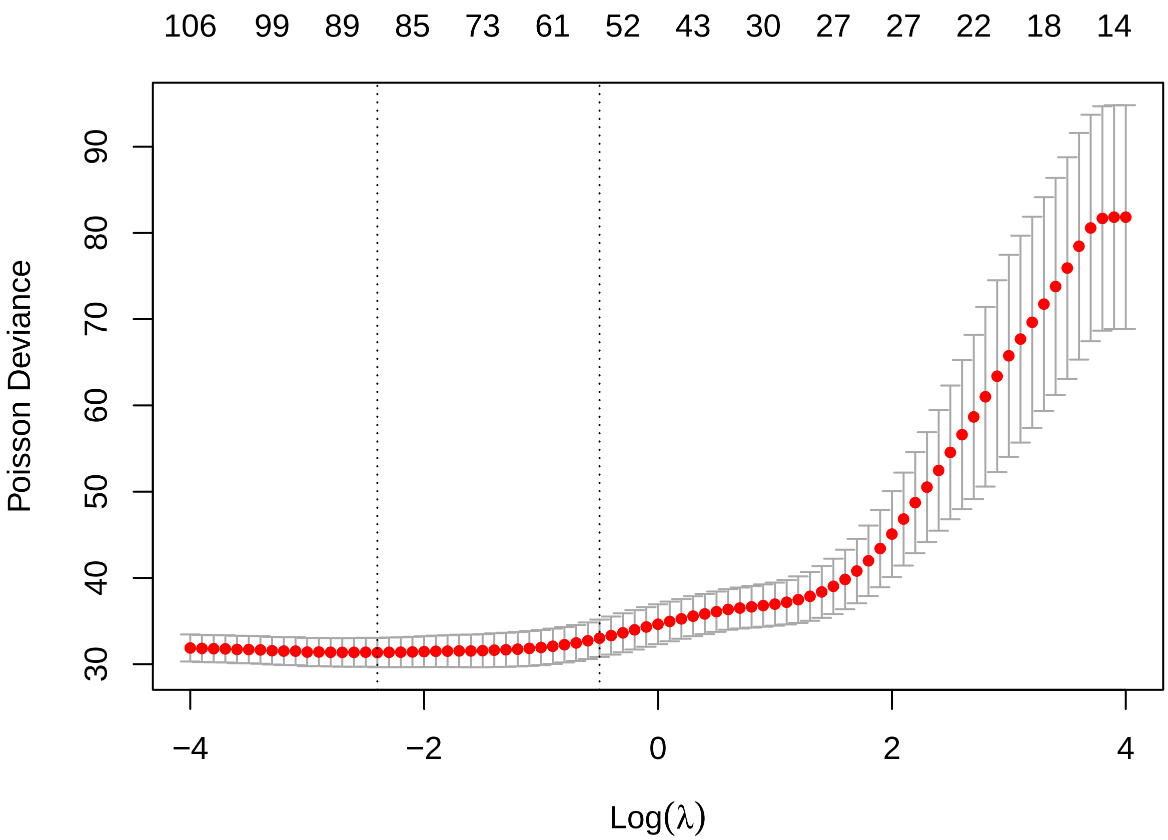


Table 9: Most Relevant Laws For Low Violance Counties [Lambda = .3]

Law	Coefficient	Proportion Occurance	Effective Deviation
REPORTALL	-0.173	0.097	0.051
COLLEGECONCEALED	0.073	0.250	0.031
UNIVERSAL	-0.072	0.177	0.027
CAPACCESS	-0.071	0.140	0.025
IMMUNITY	-0.051	0.340	0.024
ALCOHOLISM	0.061	0.120	0.020
AGE18LONGGUNPOSSESS	-0.032	0.240	0.014
MENTALHEALTH	-0.036	0.180	0.014
FINGERPRINT	-0.032	0.180	0.012
COLLEGE	0.022	0.360	0.010
OPENCARRYH	0.002	0.067	0.000

Model for Gun Violence in the US (number of people incident more than 50, high violence):





It is interesting that in our high violence model that the laws play a much more impactful role then in the low violence model.

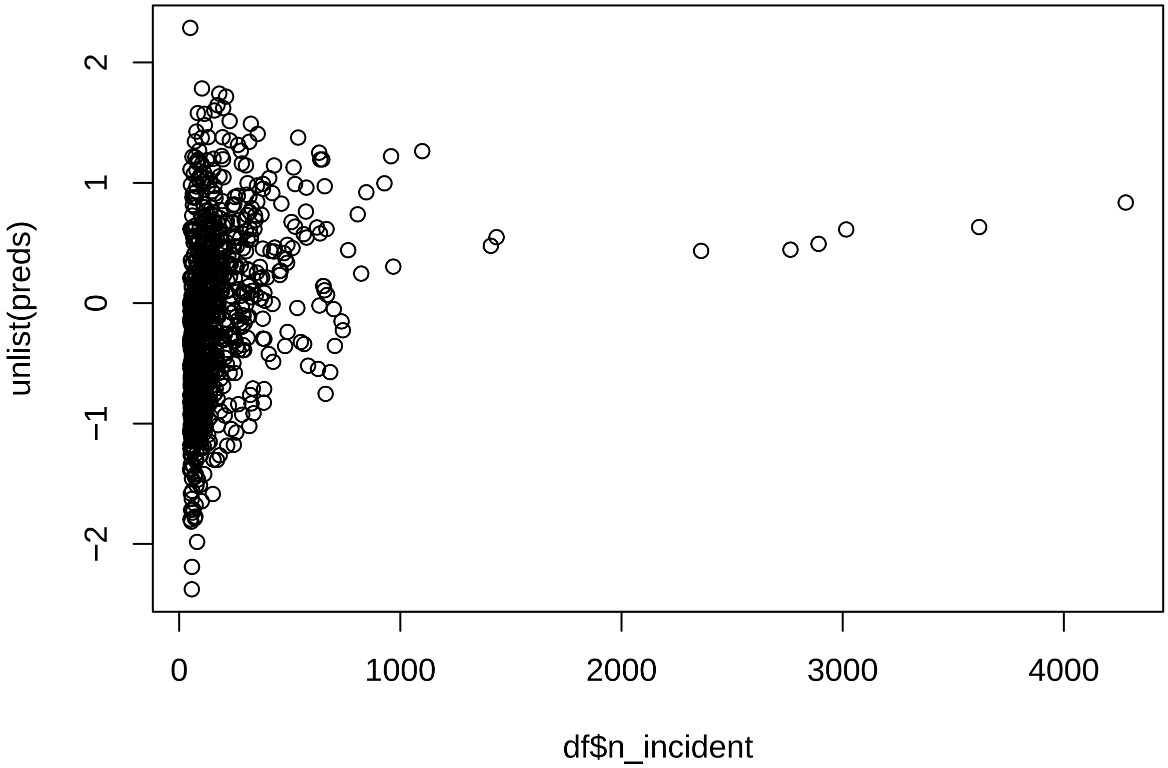


Table 10: Most Relevant Laws For High Violance Counties [Lambda = 10]

Law	Coefficient	Proportion Occurance	Effective Deviation
AMMPERMIT	0.622	0.060	0.148
REGISTRATIONH	-0.369	0.060	0.088
AGE18LONGGUNPOSSESS	-0.191	0.240	0.082
UNIVERSAL	-0.173	0.177	0.066
PREEMPTIONNARROW	-0.191	0.140	0.066
EXPARTE	-0.080	0.193	0.032
PERSONALIZED	0.117	0.040	0.023
WAITINGH	0.062	0.170	0.023
LOCKSTANDARDS	-0.073	0.060	0.017
CAPACCESS	-0.032	0.140	0.011
AMMBACKGROUND	0.002	0.060	0.001

Conclusions and Recommendations

For both the gun traffic and gun violence problems we have devised a set of models which fit the data relatively well. From each of these models we extracted the 10 or so most desired laws by the model according to the growing lasso parameter. We interpret these laws as those which have the most consistent and long-staying effect in the model. We also included trace and cross validated error plots to help the reader access model fit and how the coefficients of our given laws develop as λ varies.

We hope that this could be a starting ground to understand the root cause of gun violence and trafficking in America. A good next step would be to do a deeper survey of the laws recommended here and attempt to gain access to more diverse data sources such as:

- The number of gun stores in a county
- The type of guns traces state to state
- The sentiments of citizens in each county towards guns
- The number of gun shows along state boarder

This is an already rich topic and we hope to see more data driven approaches to reducing gun violence in American in the future.

Appendix

PCA Eigenvector Table

Table 11: Eigenvector Table, Magnitude

Names	PC1	PC2	PC3	PC4	PC5	PC6	PC7
FELONY	0.02	-0.04	0.01	-0.08	0.02	-0.09	0.03
INVCOMMITMENT	0.07	0.04	0.02	-0.03	-0.05	0.03	0.08
INVOUTPATIENT	0.07	0.07	0.06	-0.14	0.02	0.1	-0.04
DANGER	0.07	0.04	0.02	-0.03	-0.05	0.04	0.07
DRUGMISDEMEANOR	0.09	0.02	0.08	-0.09	0.03	0.03	0.07
ALCTREATMENT	0.03	-0.16	0.15	-0.01	0.01	0.03	0.07
ALCOHOLISM	0	-0.04	-0.09	0.08	-0.07	-0.13	-0.01
RELINQUISHMENT	0.1	-0.02	0.05	-0.15	0.04	-0.04	-0.11
VIOLENT	0.1	0.03	0.08	0.12	-0.12	-0.13	-0.05
VIOLENTH	0.1	0.03	0.08	0.12	-0.12	-0.13	-0.05
VIOLENTPARTIAL	0.1	0.03	0.01	0.01	-0.01	0	0.06
DEALER	0.1	-0.02	0.06	0.03	-0.11	0.13	-0.04
DEALERH	0.1	0.07	0.01	0.04	-0.06	0.08	-0.03
RECORDSALL	0.07	0.1	-0.08	-0.13	-0.17	-0.05	0.08
RECORDSALLH	0.09	0.21	-0.07	-0.04	-0.06	0.06	0.05
RECORDSDEALER	0.07	0.02	-0.09	-0.13	-0.17	0.06	0.02
RECORDSDEALERH	0.09	0.11	-0.08	-0.08	-0.04	0.09	0.03
REPORTALL	0.11	-0.08	0.01	-0.03	-0.12	-0.05	-0.12
REPORTALLH	0.1	0.04	0.03	0.07	-0.09	0.11	-0.09
REPORTDEALER	0.09	-0.05	0	-0.04	-0.14	-0.01	-0.1
REPORTDEALERH	0.11	0.06	0	0.05	-0.02	0.06	-0.12
PURGE	0.11	0.06	0.01	0.06	0.01	0.04	-0.13
RESIDENTIAL	0.06	-0.23	-0.07	-0.06	0.05	0.19	-0.06
THEFT	0.09	-0.2	-0.15	0.04	-0.08	-0.02	-0.01
SECURITY	0.09	-0.03	-0.06	0.06	-0.05	0.1	0.09
INSPECTION	0.06	-0.12	-0.04	-0.06	-0.06	0.23	-0.03
AMMLICENSE	0.06	-0.13	-0.07	-0.06	-0.04	0.14	-0.04
AMMRECORDS	0.07	-0.04	-0.14	0.12	-0.15	-0.22	0.05

PERMIT	0.12	-0.02	0.07	-0.04	-0.02	0.04	-0.04
PERMITH	0.12	0.05	0.05	-0.01	0.06	0.04	-0.02
FINGERPRINT	0.12	0.03	0	0.08	0.04	-0.01	-0.1
TRAINING	0.12	-0.04	0.04	0.07	-0.14	0.03	-0.06
PERMITLAW	0.1	0.06	0.1	-0.05	0.11	0.11	-0.04
REGISTRATION	0.04	-0.03	0.3	0	-0.07	-0.09	-0.14
REGISTRATIONH	0.04	0.05	0.14	-0.02	0.08	-0.1	-0.18
DEFACTOREG	0.1	-0.18	0.05	0.04	-0.1	-0.07	-0.09
DEFACTOREGH	0.1	0.03	0.03	0.1	0.01	0.07	-0.09
AMMPERMIT	0.08	-0.08	-0.04	-0.19	0.05	0.07	-0.02
AMMRESTRICT	0.11	0.03	0.02	0	0.06	-0.04	-0.01
AGE21HANDGUNSALE	0.1	0.05	0.02	0.06	0.01	0.03	-0.05
AGE18LONGGUNSALE	0.06	0.01	0.04	0.09	-0.06	0.09	-0.05
AGE21LONGGUNSALED	0.04	-0.02	0.23	0.01	-0.1	-0.12	-0.12
AGE21LONGGUNSALE	0.04	-0.02	0.23	0.01	-0.1	-0.12	-0.12
AGE21HANDGUNPOSSESS	0.1	0.05	0.08	0.06	0.09	0.13	-0.1
AGE18LONGGUNPOSSESS	0.05	0	0.1	-0.03	0	0.16	-0.1
AGE21LONGGUNPOSSESS	0.06	-0.23	-0.07	-0.06	0.05	0.19	-0.06
LOSTSTOLEN	0.1	0.06	-0.06	-0.09	0.07	0.05	0
AMM18	0.09	-0.03	-0.08	0.07	-0.1	0.08	0
AMM21H	0.1	0.04	-0.08	0.11	0.05	0.07	-0.03
UNIVERSAL	0.07	0.17	-0.11	-0.11	-0.12	-0.03	0.01
UNIVERSALH	0.08	0.2	-0.1	-0.03	-0.13	0.04	0.04
GUNSHOW	0.07	0.17	-0.1	-0.18	-0.1	-0.05	0.04
GUNSHOWH	0.08	0.2	-0.08	-0.09	-0.12	0.02	0.07
UNIVERSALPERMIT	0.11	0.1	0	-0.13	-0.04	0.03	-0.02
UNIVERSALPERMITH	0.11	0.12	0.02	-0.08	-0.03	0.09	0
BACKGROUNDPURGE	0.11	0.09	0.01	-0.06	0.02	0.02	-0.01
AMMBACKGROUND	0.08	-0.08	-0.04	-0.19	0.05	0.07	-0.02
THREEDAYLIMIT	0.09	-0.01	0.07	-0.06	-0.15	0.05	0.06
MENTALHEALTH	0.1	0.05	-0.12	-0.17	-0.06	0	0
STATECHECKS	0.11	0.04	0.03	-0.09	-0.08	0.07	-0.02
STATECHECKSH	0.1	0.07	0.04	-0.04	-0.06	0.12	0
WAITING	0.07	0	0.12	-0.05	-0.17	-0.13	0.02
WAITINGH	0.08	0.05	0.14	0.1	-0.09	0.01	0.17
ASSAULT	0.12	0.02	-0.11	0.12	0.11	0.01	-0.05
ONEFEATURE	0.09	0.08	-0.14	0	0.04	-0.22	-0.08
ASSAULTLIST	0.12	0.02	-0.11	0.12	0.11	0.01	-0.05
ASSAULTREGISTER	0.1	0.12	-0.11	0.08	0.13	-0.12	-0.06
ASSAULTTRANSFER	0.09	0.1	-0.11	0.1	0.02	-0.15	-0.03
MAGAZINE	0.11	0.05	-0.11	0.09	0.09	0.01	-0.03
TENROUNDLIMIT	0.12	0	-0.13	0.08	0.07	-0.03	-0.05
MAGAZINEPREOWNED	0.07	0.11	-0.06	0.11	0.2	-0.07	-0.05
ONEPERMONTH	0.08	0.07	-0.05	0.28	0	-0.01	0.07
TRAFFICKINGBACKGROUND	0.09	-0.2	-0.15	0.04	-0.08	-0.02	-0.01
TRAFFICKINGPROHIBITED	0.06	-0.03	-0.09	-0.12	0.06	-0.11	0.12
TRAFFICKINGPROHIBITEDH	0.06	-0.03	-0.09	-0.12	0.08	-0.11	0.11
STRAWPURCHASE	0.09	-0.2	-0.15	0.04	-0.08	-0.02	-0.01
STRAWPURCHASEH	0.09	-0.09	-0.1	0.12	-0.12	0.07	0.03
MICROSTAMP	0.07	-0.03	-0.13	0.14	-0.15	-0.2	0.05
GVRO	0.06	0.02	-0.08	0.01	-0.08	0.01	0.05

GVROLAWENFORCEMENT	0.06	0.06	-0.07	-0.03	-0.09	0	0
COLLEGE	0.04	-0.03	-0.08	-0.05	0.16	-0.08	0.01
COLLEGECONCEALED	0.05	-0.05	-0.06	-0.03	0.21	-0.07	0
ELEMENTARY	0.02	0.02	-0.05	-0.05	0.18	0.05	0.11
OPENCARRYH	0.01	0.03	-0.04	-0.02	0.17	-0.12	-0.05
OPENCARRYL	0.1	-0.1	0.05	-0.1	-0.04	-0.11	-0.05
OPENCARRYPERMITH	0.08	-0.03	0.05	0.04	0.07	-0.06	0.05
OPENCARRYPERMITL	0.09	-0.08	0.07	-0.02	0.04	-0.06	0.07
PERMITCONCEALED	0.05	0.04	0.02	-0.05	0.08	0.01	0.11
MAYISSUE	0.13	0.06	0.01	0.07	0	0.03	-0.05
SHOWING	0.09	0.13	0.06	0.14	-0.03	-0.03	0
CCBACKGROUND	0.04	0.02	0.01	-0.04	0.13	-0.03	0.09
CCBACKGROUNDNICS	0	0.03	0.13	-0.05	0.08	0.04	0.11
CCRENEWBACKGROUND	0.04	0.01	0.02	-0.02	0.13	-0.01	0.06
CCREVOKE	0.02	-0.02	-0.05	-0.07	0.16	0	0.11
NOSYG	0.07	0.06	0.01	-0.04	0.01	0.03	0.08
PERSONALIZED	0.05	0.11	0.04	0.25	0.11	0.15	0.05
LOCKD	0.11	0.07	-0.07	0.02	0.02	0.09	-0.02
LOCKP	0.11	-0.05	-0.11	0.07	0.04	0.04	-0.05
LOCKED	0.06	-0.23	-0.07	-0.06	0.05	0.19	-0.06
LOCKSTANDARDS	0.1	-0.11	-0.16	0.01	0.06	-0.09	-0.07
CAPLIABILITY	0.09	-0.14	-0.06	0.14	-0.05	0.01	0.18
CAPACCESS	0.09	-0.1	0.09	0.18	0.03	0.01	0.1
CAPUSES	0.09	-0.02	0.1	0.01	0.01	0.03	0.18
CAPUNLOADED	0.08	-0.11	0.15	0.07	-0.03	0.11	-0.08
CAP18	0.07	-0.12	-0.06	-0.03	-0.04	-0.03	0.2
CAP16	0.09	-0.02	0.08	0.07	-0.02	0.03	0.13
CAP14	0.09	-0.02	0.1	0.01	0.01	0.03	0.18
JUNKGUN	0.1	-0.13	0.1	0.04	-0.05	-0.05	0.14
LIABILITY	0.04	0.09	-0.04	-0.07	-0.06	0.05	-0.05
IMMUNITY	0.09	0.02	0.05	0.02	0.05	0.02	0.04
PREEMPTION	0.1	0	0.07	-0.01	0.18	0.04	-0.18
PREEMPTIONNARROW	0.11	-0.02	0.01	0.04	0.12	-0.06	-0.14
PREEMPTIONBROAD	0.12	-0.01	0.03	-0.04	0.12	-0.08	-0.09
MCDV	0.07	0.06	0.02	-0.03	-0.01	0.04	0.08
MCDVDATING	0.09	0.02	0.04	0.01	0.02	0	0.04
MCDVSURRENDER	0.1	0.01	0.04	-0.06	0.03	-0.02	0.08
MCDVSURRENDERNOCONDITIONS	0.1	0	0.02	0	0.01	-0.02	0.05
MCDVSURRENDERDATING	0.12	-0.03	0.06	-0.04	0.05	-0.07	0.06
MCDVREMOVALALLOWED	0.04	0.01	0.22	0.02	0	0.03	0.1
MCDVREMOVALREQUIRED	0.01	-0.06	0.07	0.03	0.04	-0.02	0.31
INCIDENTREMOVAL	0.03	0	0.06	0.04	-0.02	-0.08	-0.02
INCIDENTALL	0.03	0.09	0.03	0.16	0.18	0.13	0.01
DVRO	0.08	0.03	0.05	-0.05	0.04	0	0.16
DVRODATING	0.09	-0.01	0.07	0	0.09	-0.04	0.14
EXPARTE	0.09	-0.05	0.03	-0.11	0.04	-0.11	-0.05
EXPARTEDATING	0.09	-0.08	0.03	-0.09	0.06	-0.15	-0.05
DVROSURRENDER	0.1	0.01	0.07	-0.05	0.05	-0.01	0.13
DVROSURRENDERNOCONDITIONS	0.1	-0.01	0.07	-0.03	0.06	-0.06	0.13
DVROSURRENDERDATING	0.11	-0.03	0.08	-0.01	0.07	-0.06	0.11
EXPARTESURRENDER	0.11	-0.04	0.03	-0.14	0.03	-0.1	-0.06

EXPARTESURRENDERNOCONDITIONS	0.11	-0.07	0.03	-0.12	0.06	-0.15	-0.06
EXPARTESURRENDERDATING	0.11	-0.07	0.03	-0.12	0.06	-0.15	-0.06
DVROREMOVAL	0.09	-0.16	-0.06	0.09	0.02	0.01	0.17
STALKING	0.09	0.05	-0.01	-0.01	0.02	0.01	0.11

Table 12: Eigenvector Table, Sign

Names	PC1	PC2	PC3	PC4	PC5	PC6	PC7
FELONY	1	0	1	0	1	0	1
INVCOMMITMENT	1	1	1	0	0	1	1
INVOUTPATIENT	1	1	1	0	1	1	0
DANGER	1	1	1	0	0	1	1
DRUGMISDEMEANOR	1	1	1	0	1	1	1
ALCTREATMENT	1	0	1	0	1	1	1
ALCOHOLISM	1	0	0	1	0	0	0
RELINQUISHMENT	1	0	1	0	1	0	0
VIOLENT	1	1	1	1	0	0	0
VIOLENTH	1	1	1	1	0	0	0
VIOLENTPARTIAL	1	1	1	1	0	0	1
DEALER	1	0	1	1	0	1	0
DEALERH	1	1	1	1	0	1	0
RECORDSALL	1	1	0	0	0	0	1
RECORDSALLH	1	1	0	0	0	1	1
RECORDSDEALER	1	1	0	0	0	1	1
RECORDSDEALERH	1	1	0	0	0	1	1
REPORTALL	1	0	1	0	0	0	0
REPORTALLH	1	1	1	1	0	1	0
REPORTDEALER	1	0	1	0	0	0	0
REPORTDEALERH	1	1	1	1	0	1	0
PURGE	1	1	1	1	1	1	0
RESIDENTIAL	1	0	0	0	1	1	0
THEFT	1	0	0	1	0	0	0
SECURITY	1	0	0	1	0	1	1
INSPECTION	1	0	0	0	0	1	0
AMMLICENSE	1	0	0	0	0	1	0
AMMRECORDS	1	0	0	1	0	0	1
PERMIT	1	0	1	0	0	1	0
PERMITH	1	1	1	0	1	1	0
FINGERPRINT	1	1	1	1	1	0	0
TRAINING	1	0	1	1	0	1	0
PERMITLAW	1	1	1	0	1	1	0
REGISTRATION	1	0	1	1	0	0	0
REGISTRATIONH	1	1	1	0	1	0	0
DEFACTOREG	1	0	1	1	0	0	0
DEFACTOREGH	1	1	1	1	1	1	0
AMMPERMIT	1	0	0	0	1	1	0
AMMRESTRICT	1	1	1	0	1	0	0
AGE21HANDGUNSALE	1	1	1	1	1	1	0
AGE18LONGGUNSALE	1	1	1	1	0	1	0
AGE21LONGGUNSALED	1	0	1	1	0	0	0

AGE21LONGGUNSALE	1	0	1	1	0	0	0
AGE21HANDGUNPOSSESS	1	1	1	1	1	1	0
AGE18LONGGUNPOSSESS	1	1	1	0	0	1	0
AGE21LONGGUNPOSSESS	1	0	0	0	1	1	0
LOSTSTOLEN	1	1	0	0	1	1	0
AMM18	1	0	0	1	0	1	0
AMM21H	1	1	0	1	1	1	0
UNIVERSAL	1	1	0	0	0	0	1
UNIVERSALH	1	1	0	0	0	1	1
GUNSHOW	1	1	0	0	0	0	1
GUNSHOWH	1	1	0	0	0	1	1
UNIVERSALPERMIT	1	1	0	0	0	1	0
UNIVERSALPERMITH	1	1	1	0	0	1	0
BACKGROUNDPURGE	1	1	1	0	1	1	0
AMMBACKGROUND	1	0	0	0	1	1	0
THREEDAYLIMIT	1	0	1	0	0	1	1
MENTALHEALTH	1	1	0	0	0	1	0
STATECHECKS	1	1	1	0	0	1	0
STATECHECKSH	1	1	1	0	0	1	0
WAITING	1	0	1	0	0	0	1
WAITINGH	1	1	1	1	0	1	1
ASSAULT	1	1	0	1	1	1	0
ONEFEATURE	1	1	0	1	1	0	0
ASSAULTLIST	1	1	0	1	1	1	0
ASSAULTREGISTER	1	1	0	1	1	0	0
ASSAULTTRANSFER	1	1	0	1	1	0	0
MAGAZINE	1	1	0	1	1	1	0
TENROUNDLIMIT	1	0	0	1	1	0	0
MAGAZINEPREOWNED	1	1	0	1	1	0	0
ONEPERMONTH	1	1	0	1	0	0	1
TRAFFICKINGBACKGROUND	1	0	0	1	0	0	0
TRAFFICKINGPROHIBITED	1	0	0	0	1	0	1
TRAFFICKINGPROHIBITEDH	1	0	0	0	1	0	1
STRAWPURCHASE	1	0	0	1	0	0	0
STRAWPURCHASEH	1	0	0	1	0	1	1
MICROSTAMP	1	0	0	1	0	0	1
GVRO	1	1	0	1	0	1	1
GVROLAWENFORCEMENT	1	1	0	0	0	1	0
COLLEGE	1	0	0	0	1	0	1
COLLEGECONCEALED	1	0	0	0	1	0	1
ELEMENTARY	1	1	0	0	1	1	1
OPENCARRYH	1	1	0	0	1	0	0
OPENCARRYL	1	0	1	0	0	0	0
OPENCARRYPERMITH	1	0	1	1	1	0	1
OPENCARRYPERMITL	1	0	1	0	1	0	1
PERMITCONCEALED	1	1	1	0	1	1	1
MAYISSUE	1	1	1	1	0	1	0
SHOWING	1	1	1	1	0	0	1
CCBACKGROUND	1	1	1	0	1	0	1
CCBACKGROUNDNICS	0	1	1	0	1	1	1
CCRENEWBACKGROUND	1	1	1	0	1	0	1

CCREVOKE	1	0	0	0	1	0	1
NOSYG	1	1	1	0	1	1	1
PERSONALIZED	1	1	1	1	1	1	1
LOCKD	1	1	0	1	1	1	0
LOCKP	1	0	0	1	1	1	0
LOCKED	1	0	0	0	1	1	0
LOCKSTANDARDS	1	0	0	1	1	0	0
CAPLIABILITY	1	0	0	1	0	1	1
CAPACCESS	1	0	1	1	1	1	1
CAPUSES	1	0	1	1	1	1	1
CAPUNLOADED	1	0	1	1	0	1	0
CAP18	1	0	0	0	0	0	1
CAP16	1	0	1	1	0	1	1
CAP14	1	0	1	1	1	1	1
JUNKGUN	1	0	1	1	0	0	1
LIABILITY	1	1	0	0	0	1	0
IMMUNITY	1	1	1	1	1	1	1
PREEMPTION	1	1	1	0	1	1	0
PREEMPTIONNARROW	1	0	1	1	1	0	0
PREEMPTIONBROAD	1	0	1	0	1	0	0
MCDV	1	1	1	0	0	1	1
MCDVDATING	1	1	1	1	1	1	1
MCDVSURRENDER	1	1	1	0	1	0	1
MCDVSURRENDERNOCONDITIONS	1	0	1	1	1	0	1
MCDVSURRENDERDATING	1	0	1	0	1	0	1
MCDVREMOVALALLOWED	1	1	1	1	1	1	1
MCDVREMOVALREQUIRED	1	0	1	1	1	0	1
INCIDENTREMOVAL	1	1	1	1	0	0	0
INCIDENTALL	1	1	1	1	1	1	1
DVRO	1	1	1	0	1	0	1
DVRODATING	1	0	1	1	1	0	1
EXPARTE	1	0	1	0	1	0	0
EXPARTEDATING	1	0	1	0	1	0	0
DVROSURRENDER	1	1	1	0	1	0	1
DVROSURRENDERNOCONDITIONS	1	0	1	0	1	0	1
DVROSURRENDERDATING	1	0	1	0	1	0	1
EXPARTESURRENDER	1	0	1	0	1	0	0
EXPARTESURRENDERNOCONDITIONS	1	0	1	0	1	0	0
EXPARTESURRENDERDATING	1	0	1	0	1	0	0
DVROREMOVAL	1	0	0	1	1	1	1
STALKING	1	1	0	0	1	1	1