The Effect of State Domestic Violence Laws on Intimate Partner Homicide Compared to the 1996 Gun Control Amendment

Michelle Zhang, Grace Deng, Anusha Mittal

2022-12-05

Abstract

In this paper, we aim to identify the different states that originally had 0 domestic violence state laws passed before 1996 and passed more state laws regarding domestic violence gun laws after the 1996 Lautenberg Amendment was passed, which implemented stronger IPH firearm laws, and states that continued to just rely on federal law when it came to domestic violence and gun control laws, which implemented weaker IPH firearms, between the years 1996 and 2005 (after the 1996 federal law was implemented.)

Background

Over 50,000 people have been killed by intimate partners. Over 50% of intimate partner homicide (IPH) involved firearms. Over the years, states have implemented various strengths of gun control regulations to combat IPH. In 1996, the The US passed the Lautenberg Amendment to the Gun Control Act in the 1996, prohibiting Yet, states have varying levels of gun restriction policies to combat IPH, with some states choosing to further support this legislation while others do not. Stronger laws include forfeiture of firearms for those with domestic violence restraining orders, past domestic violence convictions, or those found at the scene of a domestic violence occurrence. Weaker laws include limiting the type of guns a perpetrator may be able to carry.

When thinking about the term "gun violence," a lot comes to mind. Gun violence is a very broad term that encompasses so many different topics such as type, causes, and even solutions. Some types of gun violence that are talked about and shown on media are mass shootings, suicides, and domestic violence. In addition to types, many causes of gun violence are also talked about. Mental illness is a big topic relating to gun violence. Is the individual with the gun mentally stable enough to be able to hold the firearm? There is also relatively easy access to firearms and a lack of gun industry accountability. Are there just guns lying around in a household where any member in that household is able to access it? What criteria needs to be met in order for a firearm to be sold to an individual and are there middlemen that are allowing individuals to skip any of the accountability steps necessary to prevent danger? These are just a few causes of firearms that are prominent in different gun violence cases we hear today. Alongside the causes of gun violence, there is constant talk about solutions in preventing gun violence. The most common one is universal background checks. The more thoroughly an individual is checked before being sold a gun, the risk of violence decreases. In the same context as background checks, there is a lot of argument on the effectiveness of waiting periods. A waiting period is the time between when a firearm is sold to an individual and when the individual receives the firearm. Many argue that the longer the waiting period is, the more time given to the seller to do thorough background checks to make sure the recipient is capable of holding the gun safely. Another example of solutions talked about are the extreme risk laws. These are laws that permit a firearm to be taken away from individuals who are deemed either harmful to themselves or those around them. With these laws in place, the risk of gun violence could be mitigated.

From these topics, the discussion of domestic violence within gun violence stood out a lot because it is a type of violence that is not shown or talked about as much in the media. Upon further research, we found that over half of mass shooting cases between the years 2014 and 2019 were related to domestic violence and the perpetrator has either killed a family member or partner before or had a history of domestic violence. Then, we read some past papers about the relationship between gun violence and domestic violence. The first one was Hold Your Fire: 1996 Amendment (Raissan) which analyzed the impact of a federal gun control expansion on intimate partner homicides using a differences in differences model. The result showed that federal gun control expansion reduced intimate homicides in both females and male domestic children. The second article we looked at was Analysis of the Strength of Legal Firearms Restrictions for Perpetrators of Domestic Violence and Their Associations With Intimate Partner Homicide (Zeoli, et al). This paper studied the effect of firearm law characteristics like breadth, strength, and systems of accountability on intimate partner homicides using a negative binomial regression model. The result showed that domestic violence restraining order firearm-prohibition laws are associated with a decrease in intimate partner homicides.

So, what were the federal laws that were mentioned in the studies above? The first was the Federal Gun Control Act enacted in 1968. This law imposed stricter regulations on the firearm industry, which restricted individuals without gun licenses from obtaining a firearm. Then, in 1996, the Lautenberg Amendment was enacted. This amendment was amended to the 1968 law, and it made it a federal felony for a person convicted of a qualifying misdemeanor crime of domestic violence to possess a firearm. The newly amended amendment was important because it enhanced restrictions to those who had a history of domestic violence. Both of these laws are important because they are federal laws which are distinct from state laws. Federal laws are retroactive and permanent, which means that there are no public service exemptions, and any penalties for violating are larger than those that would exist from state laws. There are also federal resources that come to ensure that the federal law is effective.

Question

From this background, our study looks at after the Lautenberg Amendment, did states that passed additional domestic violence gun laws experience lower intimate partner homicide (IPH) rates than states that solely relied on the federal gun expansion to combat intimate partner homicides? Our initial approach in looking at this question utilizes a differences in differences approach to identify the change in IPH between a state that was treated (did not enact state domestic violence laws before 1996 but enacted state domestic violence laws after 1996) and a state that was not treated (never enacted domestic violence laws before and after 1996).

Data Sources

We primarily used two kinds of data sources. The first pertained to our treatment groups where we explored databases giving us more insight into intimate partner homicide rates and the second included control variables that had data we wanted to control for.

State Firearm Laws by State-Year This data used the Thomson Reuters Westlaw data to access historical state statutes/laws wherein the dataset indicates the presence of 133 firearm provisions across states. For the control variables we used 2 more datasets to control for demographic data. The State population data by year was gathered through the US Census Bureau dataset and for the State unemployment data by year we used the Local Area Unemployment Statistics, U.S. Bureau of Labor Statistics (BLS) dataset. Further, to control in the original Siegel dataset we came across other firearm-related laws that could pertain to domestic violence offenders but were not IPH related that we needed to control for. These laws included state high-risk gun possession laws that prohibited "high-risk" individuals from possessing guns due to history of mental health issues, drug/alcohol misuse, criminal activity and essentially anything other than DM offenses.

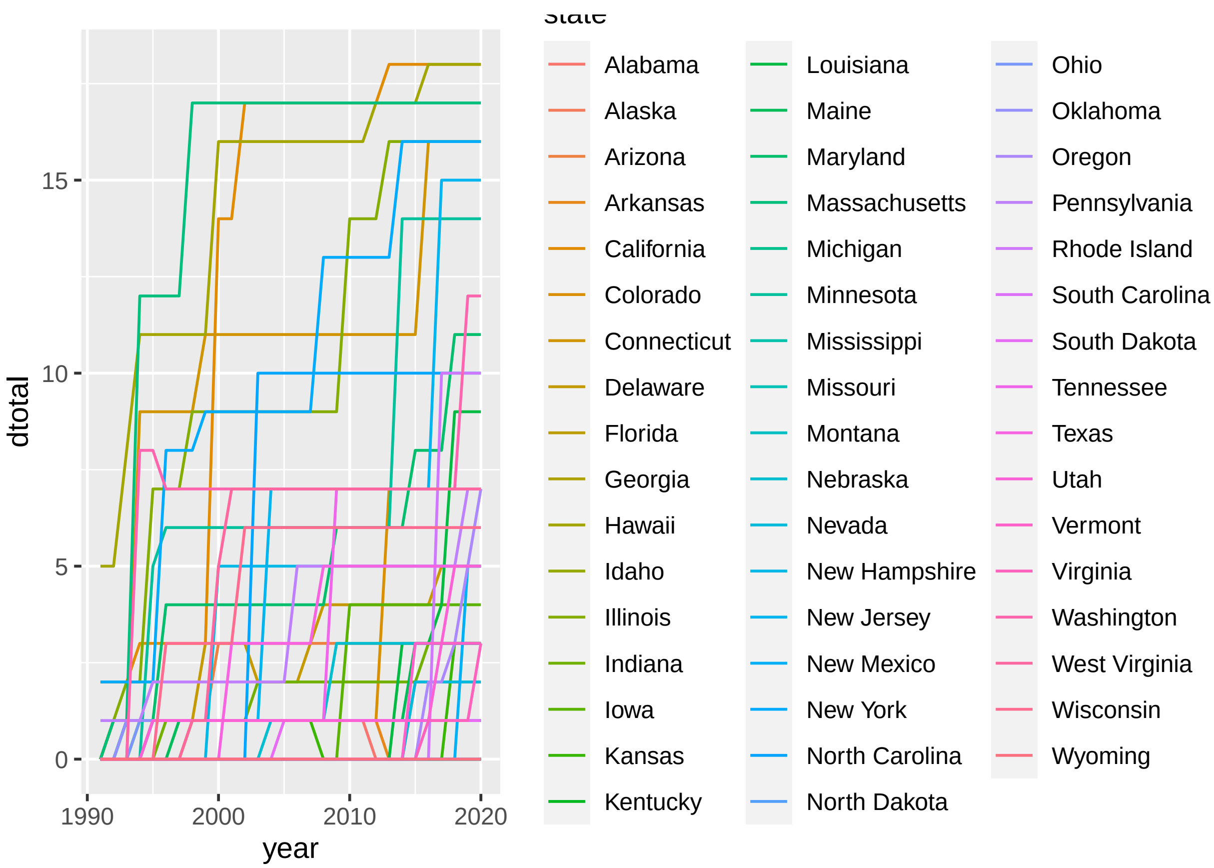
Intimate Partner Homicide Rates by State-Year To find IPH rates we used the FBI supplemental Homicide reports which was the only national data set that we found that records homicide victim-offender relationships helping us sort which cases were domestic violence related. While this was a great data source, due to voluntary participation by state and local law enforcement 1/3 of the data was missing which would lead to inaccurate analysis if used. Hence, we used the Multiple Imputation of the Supplementary Homicide Reports, 1976 - 2005 (James Fox, Marc Swatt) where the missing data was imputed by Fox and Swatt using known variables about cases. The imputed data set included the necessary observed associations of the variables where victim-offender relationships were clear enough for us to analyze. The second data set we used was to gather data on state domestic violence firearm laws by state and year for which we used the Firearm-Related Laws in All 50 US States, 1991 - 2016 (Michael Siegel).

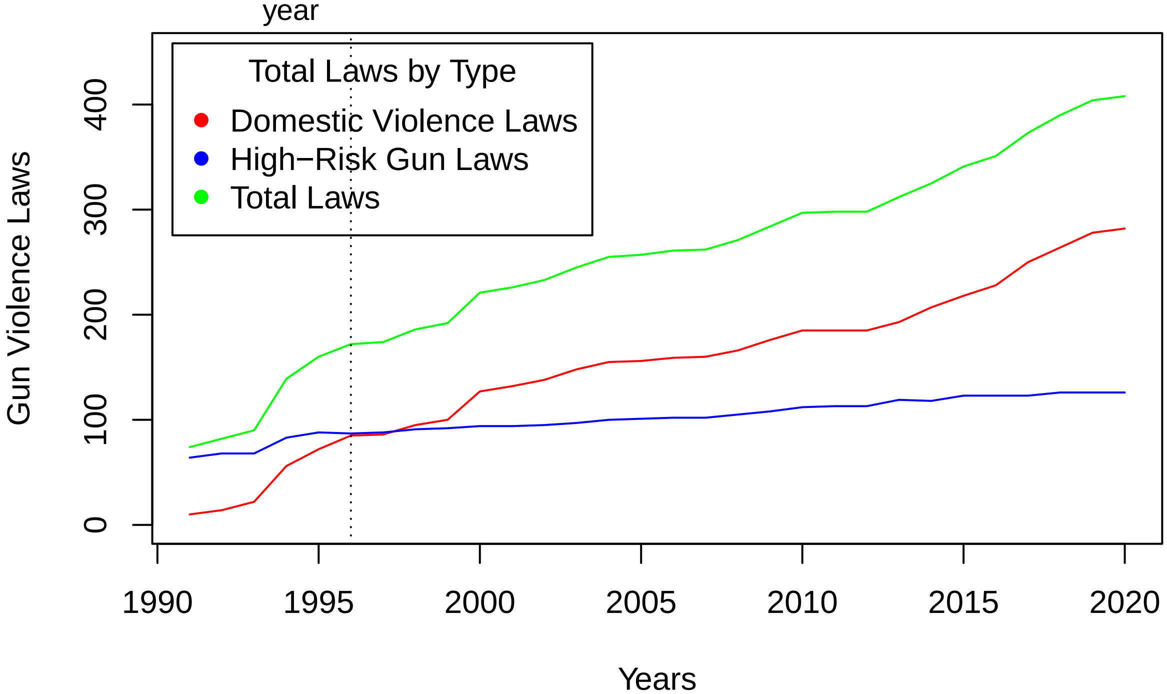
Population by State-Year State population data was acquired from the U.S. Census Bureau and used as a control since intimate partner homicides were recorded by count.

Unemployment by State-Year State unemployment data was acquired from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics. This data was used to control for poverty as a confounding factor for domestic violence.

Data Cleaning

State Firearm Laws by State-Year We created a data frame consisting solely of firearm state laws that were categorized as "domestic violence" or "high-risk gun possession" related (used as a control later). To see the state firearm law trend relating to these categories, we plotted the total laws by year. There seems to be a drastic increase in total domestic violence state firearm laws from 1994 to 1996, and much smaller increases right after 1996. While the increase is very large, the increase means a differences-in-differences analysis can still be conducted.





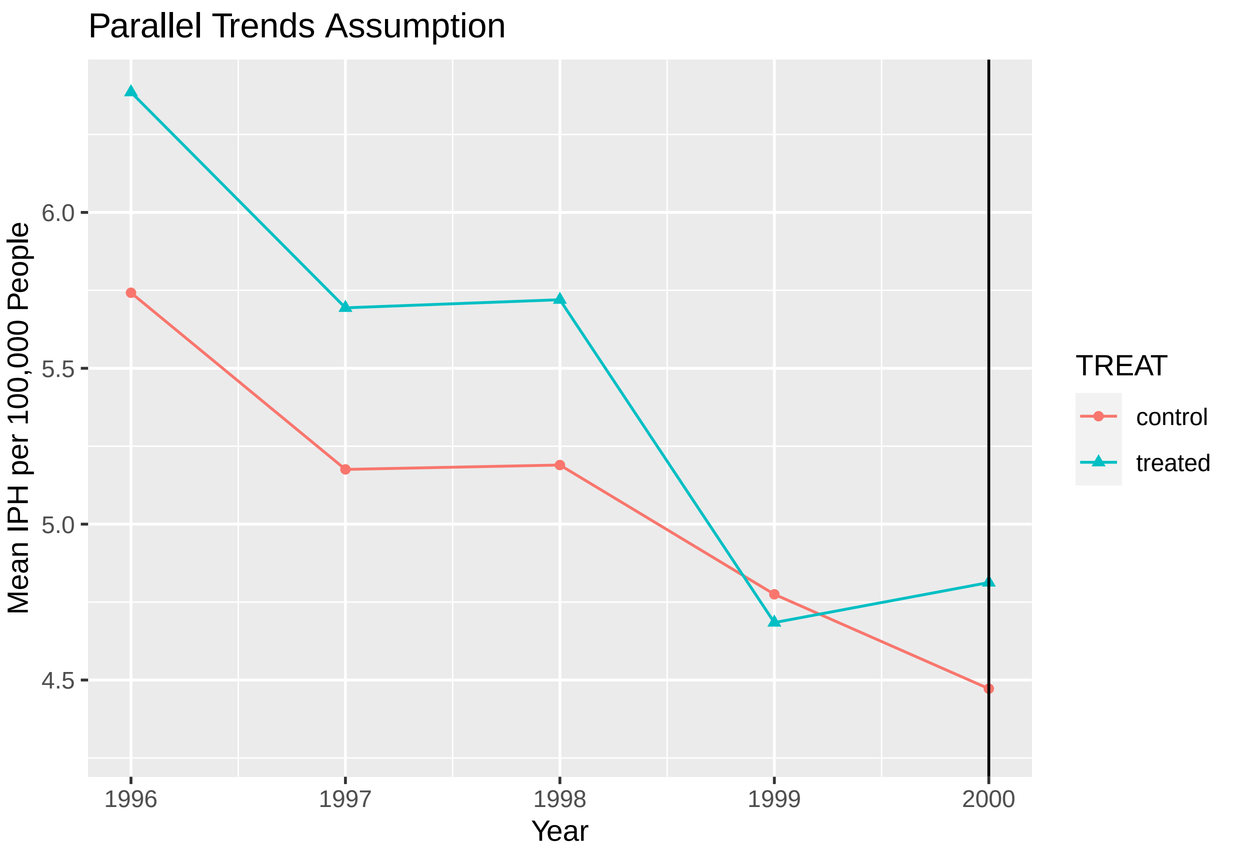
Intimate Partner Homicide Rates by State-Year We cleaned this data set to only have intimate partner homicides occurring in our study period - 1996 to 2005. States that had 0 state domestic violence laws from 1996 to 2005 were placed in our control group, and states that had 0 state domestic violence laws in 1996 and more than 1 state domestic violence law in 2001 were placed in our treatment group. All other state-year combinations were excluded. This left only one state - TX - in our treatment group and 14 states (AK, GA, ID, IA, KY, LA, MI, MS, MO, NV, NM, OR, RI, SC, VA) in our control group.

Data Analysis

```
## Warning: Removed 10 rows containing non-finite values (`stat_summary()`).
```

```
## No summary function supplied, defaulting to `mean_se()`
```

```
## Warning: Removed 10 rows containing missing values (`geom_point()`).
```



Plotting the mean intimate partner homicide (IPH) rates per year by control/treatment group shows that the parallel trend assumption seems to hold prior to 1996. By assuming this parallel trend would continue in a counterfactual treatment group, we are able to calculate the differences-in-differences to show a causal relationship (given it is statistically significant) that is. The following two figures demonstrate the parallel trend assumption and the differences-in-differences between the control and treatment group.

The average treatment effect (ATT) is -0.2339732, implying that the rate of IPH per 100,000 people for states that implemented their own domestic violence laws was 0.2339732 less than for states that relied solely on the federal domestic violence gun law expansion (Lautenberg Amendment). However, this does not relay any information regarding the statistical significance of this result. In order to attain this, we employed several regressions.

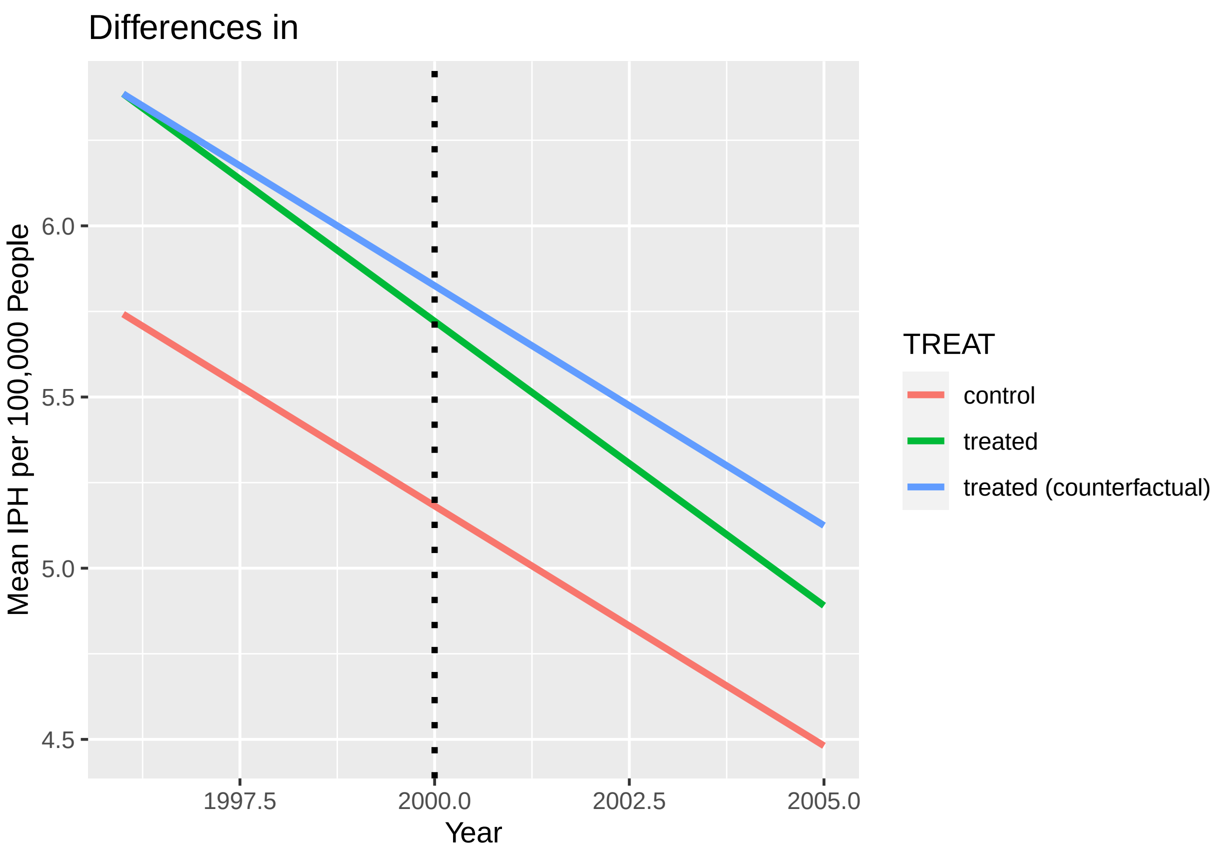
```
## # A tibble: 1 x 3
##   variable control treated
```

```
##   <chr>       <dbl>   <dbl>
## 1 IPH_CAP      5.74    6.39
```

```
## # A tibble: 1 x 3
##   variable control treated
##   <chr>       <dbl>   <dbl>
## 1 IPH_CAP      4.48    4.89
```

```
## `summarise()` has grouped output by 'TIME'. You can override using the
## `.groups` argument.
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
```



####Linear regression

```
##
## Call:
## lm(formula = IPH_CAP ~ time * treat, data = did)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.979 -1.339   0.140   1.027   6.006
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)   5.7422     0.5803   9.896 1.21e-10 ***
## time         -1.2610     0.8206  -1.537    0.136
## treat         0.6434     2.3211   0.277    0.784
## time:treat   -0.2340     3.2826  -0.071    0.944
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.247 on 28 degrees of freedom
## Multiple R-squared:  0.08751,    Adjusted R-squared:  -0.01026
## F-statistic: 0.8951 on 3 and 28 DF,  p-value: 0.4559

##                 2.5 %   97.5 %
## (Intercept)  4.553595 6.930890
## time        -2.941987 0.420016
## treat       -4.111216 5.397964
## time:treat  -6.957978 6.490032

##
## Call:
## lm(formula = IPH_CAP ~ time * treat + UNEMP, data = did)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9257 -1.3376 -0.1144  1.1202  5.8309
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.59897    2.02541   1.283    0.210
## time        -1.32202    0.79889  -1.655    0.110
## treat        0.52512    2.25827   0.233    0.818
## UNEMP        0.57220    0.35411   1.616    0.118
## time:treat  -0.00128    3.19525   0.000    1.000
##
## Residual standard error: 2.185 on 27 degrees of freedom
## Multiple R-squared:  0.168,  Adjusted R-squared:  0.04471
## F-statistic: 1.363 on 4 and 27 DF,  p-value: 0.273

##
## Call:
## lm(formula = NUM_IPH ~ time * treat + POP, data = did)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -170.55  -51.25    0.00   31.39  221.72
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.182e+01  3.033e+01   1.049   0.3033
## time        -4.620e+01  3.022e+01  -1.529   0.1379
```

```
## treat        2.227e+02  1.231e+02   1.809   0.0817 .
## POP          5.070e-05  5.710e-06   8.879 1.71e-09 ***
## time:treat  -2.491e+02  1.218e+02  -2.045   0.0508 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 82.55 on 27 degrees of freedom
## Multiple R-squared:  0.9258, Adjusted R-squared:  0.9148
## F-statistic: 84.18 on 4 and 27 DF,  p-value: 7.639e-15
```

```
##
## Call:
## lm(formula = IPH_CAP ~ time + treated + time * treated, data = did_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.3882 -1.5548  0.0304  1.2400  7.3039
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.0709     0.2651  19.126   <2e-16 ***
## time          -0.4880     0.3750  -1.301    0.195
## treated        0.3884     1.0605   0.366    0.715
## time:treated  -0.1401     1.4998  -0.093    0.926
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.296 on 156 degrees of freedom
## Multiple R-squared:  0.01304,    Adjusted R-squared:  -0.005942
## F-statistic: 0.687 on 3 and 156 DF,  p-value: 0.5613
```

```
##                  2.5 %   97.5 %
## (Intercept)   4.547219 5.594658
## time         -1.228624 0.252679
## treated      -1.706522 2.483234
## time:treated -3.102709 2.822502
```

```
##
## Call:
## lm(formula = IPH_CAP ~ time + treated + time * treated + UNEMP,
##     data = did_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.4974 -1.5965  0.1072  1.1922  7.6105
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.5490     0.8252   4.301    3e-05 ***
```

```
## time          -0.7519     0.3956  -1.901   0.0592 .
## treated        0.3176     1.0518   0.302   0.7631
## UNEMP          0.3198     0.1644   1.946   0.0535 .
## time:treated  -0.1640     1.4867  -0.110   0.9123
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.276 on 155 degrees of freedom
## Multiple R-squared:  0.03657,    Adjusted R-squared:  0.01171
## F-statistic: 1.471 on 4 and 155 DF,  p-value: 0.2137
```

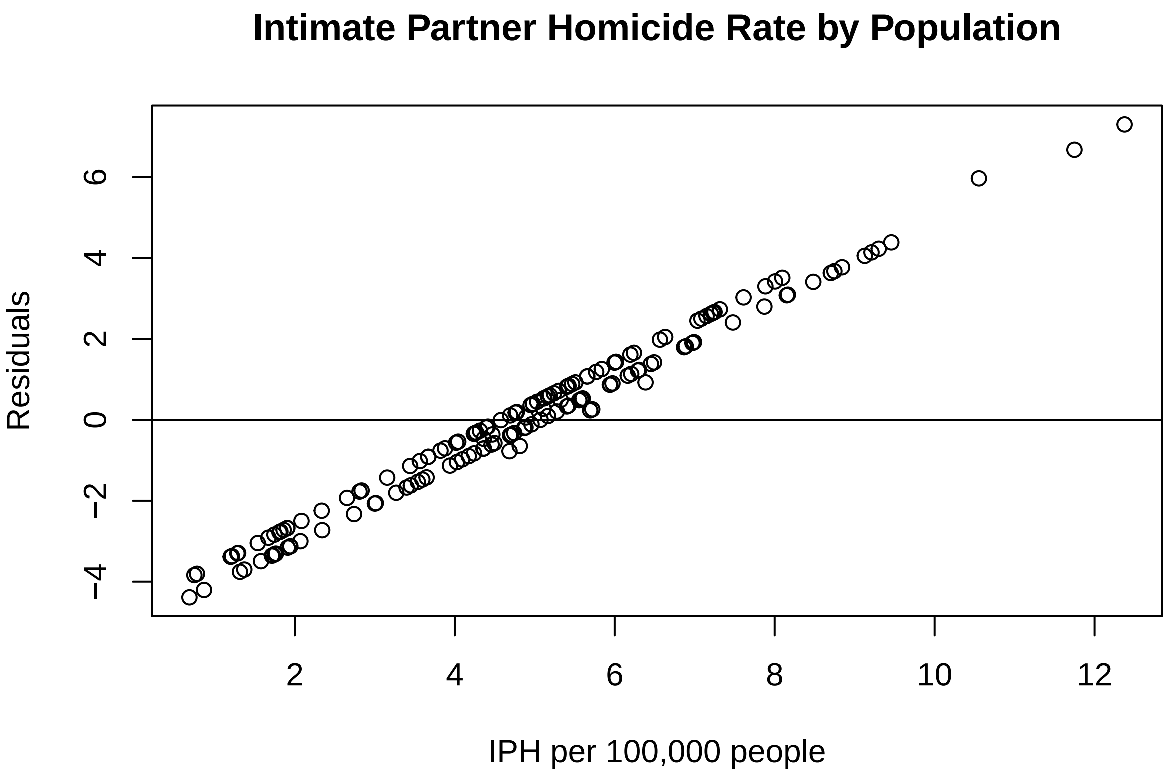
```
##
## Call:
## lm(formula = NUM_IPH ~ time * treated + POP, data = did_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -162.798  -54.524   -2.959   49.316  276.933
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.258e+01  1.399e+01   0.899   0.3700
## time         -2.314e+01  1.377e+01  -1.681   0.0948 .
## treated       7.904e+01  5.744e+01   1.376   0.1708
## POP           4.988e-05  2.597e-06  19.210   <2e-16 ***
## time:treated -1.030e+02  5.520e+01  -1.865   0.0641 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 84.24 on 155 degrees of freedom
## Multiple R-squared:  0.9001, Adjusted R-squared:  0.8975
## F-statistic: 349.2 on 4 and 155 DF,  p-value: < 2.2e-16
```

First, we began with a basic ordinary least squares regression. Using the IPH rate per 100,000 people as the outcome variable, the differences-in-differences is the same as using simple subtraction: -0.2340. The p-value of 0.944 shows that this does not have statistical significance. However, this linear regression was regressed only over two independent variables: the years 1996 and 2005. Regressing IPH rate per 100,000 people over all years in the period returned a differences-in-differences of -0.1401 and a p-value of 0.926 (still high but lower than our first regression). Controlling for unemployment brought our p-value down to 0.9123, and interaction term coefficient to -0.1640, implying that the states that have domestic violence laws have an IPH rate per 100,000 people of that amount less than states that do not (to no statistical significance).

Here, we pondered whether or not directly using the IPH rate as our outcome variable was interfering with the fit of our model. Thus, we decided to use the count of IPH as the outcome variable and control for population in the regression. This regression resulted in a differences-in-differences of -103.0 and a much lower p-value of 0.0641, which had minute statistical significance. This implies that treatment states have 103 less IPHs than control states.

Clearly, this indicated that the vastly differing population sizes amongst states in our study were interfering with our model. We plotted the residuals of the IPH rate per 100,000 people, and saw that the residuals were not vertically scattered. In fact, they had a strong, positive, linear correlation. This implies that as population size grows, the model is fitting less and less well, placing an emphasis on states with smaller populations. This rendered our linear regression analysis null because OLS assumes there is a normal distribution about expected value and that errors are uncorrelated. To explore further, we decided to do a poisson regression because it explicitly deals with count data over a time period.

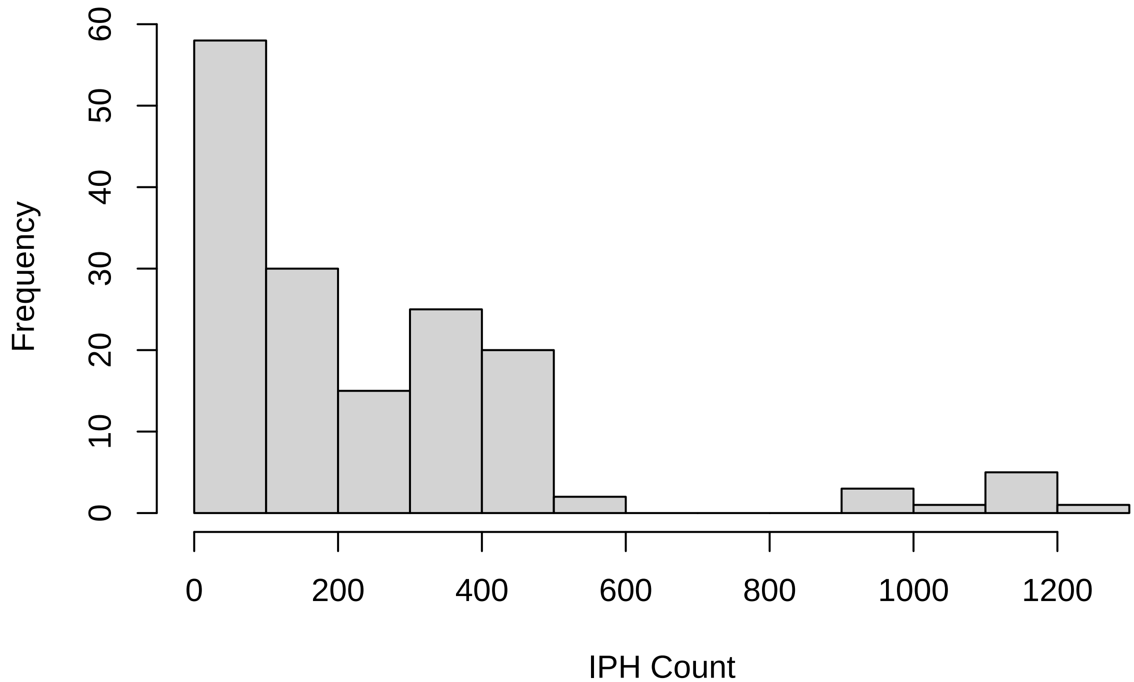
```
# plotting residuals
resid <- resid(ols1)
plot(did_df$IPH_CAP, resid,
     ylab="Residuals", xlab="IPH per 100,000 people",
     main="Intimate Partner Homicide Rate by Population") + # residuals are not evenly distribut
abline(0, 0)
```




```
## integer(0)
```

Poisson Regression The histogram below further shows the dispersion of our data. We conducted the poisson regression with population as an offset since our populations had such high variance. Taking the exp of our coefficient, the treatment group experienced 0.9973254x of IPH that the control group did at a p-value of 0.804. This was still not statistically significant, despite it being lower than the p-values of our linear regressions.

At this point, we realized that our dataset did not uphold the assumptions required for a poisson regression. The variance of our population data (2.396795e+13) was much higher than the mean (5044945). This meant that there was clear overdispersion in our data, and that we should try a different model that can accommodate for those assumptions.




```
##
## Call:
## glm(formula = NUM_IPH ~ time + treated + time * treated + offset(log(POP)),
##     family = poisson, data = did_df)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -14.4853   -5.0915   -0.4946    3.1815   16.3288
##
## Coefficients:
##               Estimate Std. Error   z value Pr(>|z|)
## (Intercept)  -9.842818   0.008050 -1222.656   <2e-16 ***
## time         -0.116425   0.011574   -10.059   <2e-16 ***
## treated       0.024163   0.015722     1.537    0.124
## time:treated -0.002678   0.022453    -0.119    0.905
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5471.3  on 159  degrees of freedom
## Residual deviance: 5328.0  on 156  degrees of freedom
## AIC: 6428.5
##
## Number of Fisher Scoring iterations: 4
```

```
## time:treated
##    0.9973254
```

```
##
## Call:
## glm(formula = NUM_IPH ~ time + treated + time * treated + offset(log(POP)) +
##     UNEMP, family = poisson, data = did_df)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -14.7704   -5.2375   -0.3822    3.1344   16.8071
##
## Coefficients:
##                Estimate Std. Error  z value Pr(>|z|)
## (Intercept)  -1.004e+01  2.422e-02 -414.612   <2e-16 ***
## time         -1.657e-01  1.289e-02  -12.854   <2e-16 ***
## treated       8.430e-05  1.595e-02    0.005    0.996
## UNEMP         4.473e-02  5.125e-03    8.727   <2e-16 ***
## time:treated  5.571e-03  2.247e-02    0.248    0.804
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 5471.3  on 159  degrees of freedom
## Residual deviance: 5251.9  on 155  degrees of freedom
## AIC: 6354.4
##
## Number of Fisher Scoring iterations: 4

## time:treated
##     1.005587

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##   608569  1872008  3704701  5044945  6030446 22778123

## [1] 5044945

## [1] 4895707

## [1] 2.396795e+13

## [1] 0
```

Negative Binomial Regression The negative binomial regression accommodates for overdispersion. Utilizing the same formula and offsetting population, our differences-in-differences implied that the treatment group experienced 0.9819674x of the control group's IPH - smaller than the poisson regression implied. However, the p-value was much higher at 0.956, most likely because this modeled allowed for the high variance in our data. Even controlling for high-risk gun possession laws and unemployment did not seem to bring the p-values significantly lower. We concluded that our unbalanced sample set (1 treated state vs 14 control states) was contributing to our inability to support any hypothesis.

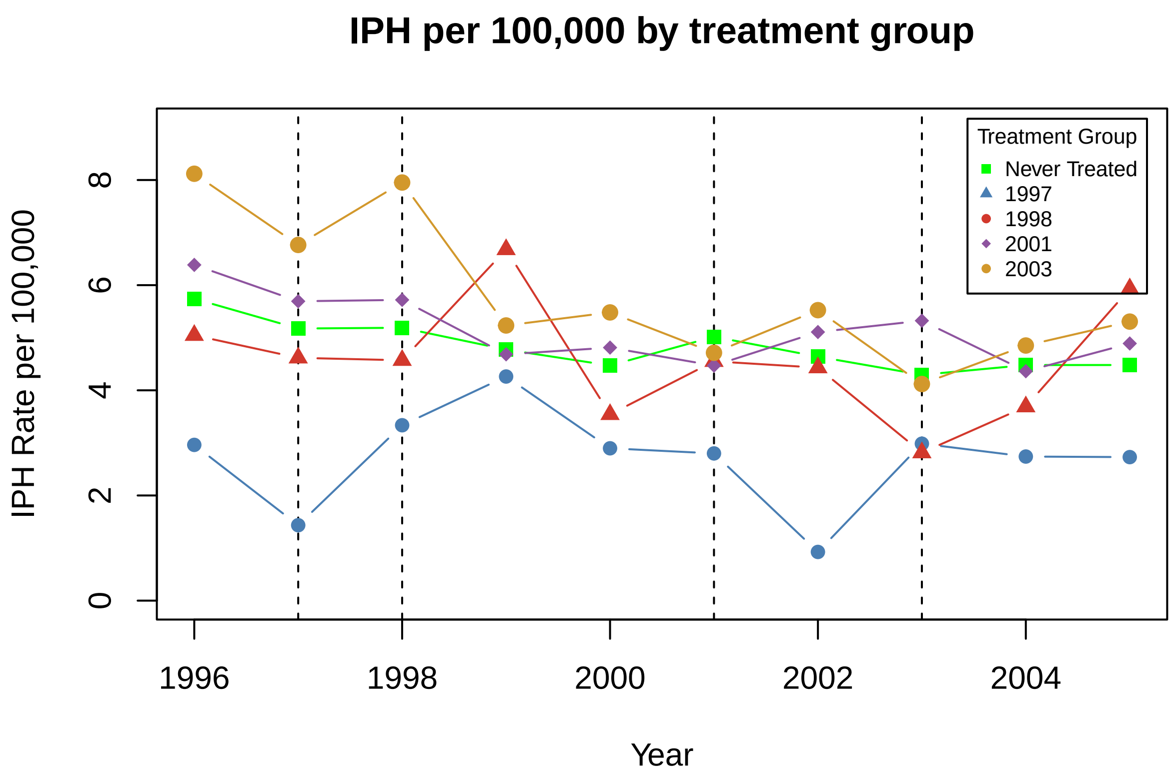
```
##
```

```
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

##
## Call:
## glm.nb(formula = NUM_IPH ~ time * treated + offset(log(POP)),
##     data = did_df, init.theta = 4.008142719, link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7862  -0.6845   0.0103   0.4742   2.0714
##
## Coefficients:
##              Estimate Std. Error  z value Pr(>|z|)
## (Intercept)  -9.88619    0.05867 -168.511   <2e-16 ***
## time         -0.10401    0.08300   -1.253    0.210
## treated       0.07057    0.23135    0.305    0.760
## time:treated -0.01820    0.32719   -0.056    0.956
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(4.0081) family taken to be 1)
##
##     Null deviance: 170.59  on 159  degrees of freedom
## Residual deviance: 168.72  on 156  degrees of freedom
## AIC: 1861.6
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  4.008
##           Std. Err.:  0.456
##
##  2 x log-likelihood:  -1851.609

##  (Intercept)         time      treated time:treated
## 5.087237e-05 9.012143e-01 1.073124e+00 9.819674e-01

##
## Call:
## glm.nb(formula = NUM_IPH ~ time * treated + offset(log(POP)) +
##     UNEMP, data = did_df, init.theta = 4.088267618, link = log)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.83332  -0.74793   0.03768   0.47103   2.28042
##
```

```
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -10.21175    0.18238 -55.991   <2e-16 ***
## time          -0.15751    0.08763  -1.797   0.0723 .
## treated        0.05564    0.22924   0.243   0.8082
## UNEMP          0.06780    0.03643   1.861   0.0628 .
## time:treated  -0.02426    0.32399  -0.075   0.9403
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(4.0883) family taken to be 1)
##
##     Null deviance: 173.8  on 159  degrees of freedom
## Residual deviance: 168.6  on 155  degrees of freedom
## AIC: 1860.3
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  4.088
##           Std. Err.:  0.466
##
##  2 x log-likelihood:  -1848.346

##  (Intercept)         time      treated        UNEMP time:treated
## 3.673614e-05 8.542651e-01 1.057218e+00 1.070147e+00 9.760315e-01
```

DID for Multiple Treatments

We used the did package to explore multiple treatments and allow for more treatment states. We hoped that this would allow for a conclusion to be drawn with differences-in-differences. In doing so, our treatment states became any state that enacted at least 1 domestic violence law after 1996. As a result, we had Maine (1997), West Virginia (1998), Texas (2001), and North Carolina (2003) as treatment states. Although ideally we would have multiple states in each treatment group (year), this was better than our previous analysis using only the state of Texas (as large and diverse as Texas is, it is much better to have more states in our sample set). Below is a chart of the IPH Rate per 100,000 people by treatment group.



The average treatment effects of each group is still inconclusive towards causality, with only a select few state-years having significance and a confidence interval that does not traverse 0 as seen by the figures below. Even grouping by exposure and group did not result in any significant results.

Conclusion

We utilized multiple regression models to try and analyze our data and find a statistically significant difference-in-differences. However, despite achieving differences that imply states that enact domestic violence laws have lower IPH counts/rates, we were unable to establish significance in any instance.

Limitations

There are some limitations that come from our study. The first limitation is that our group sizes were very small. Doing the initial differences in differences, we only had one state in the treatment group, which is a very small sample size. This small size could have created some variation in our results so that limited our results. When we did the staggered analysis and expanded the years for our treatment group, we still only had four states. While four is better than one, the size was still relatively small so it could have also created variation in our results. Also, as we tried to control more by year with our staggered analysis, we found that each of the four states passed laws in separate years so that turned our small sample of four states even smaller into one state per year per analysis.

In addition to small group sizes, we came across the problem of having insufficient data. We wanted to control for more factors that could potentially affect the IPH rates such as poverty rates, marriage rates, and education rates in each of the states, but we were unable to find the data for these factors for the years and states we were testing on. Our data was also from the 1990's and early 2000's which was a while ago, so many of the states have probably passed more domestic violence gun control laws that could have created more significance in the effect of these state laws on gun violence. We did not have the data for states past the year 2005, but if this data was present, that would have likely expanded our group sizes to be of more moderate sizes as well as produced less variation and more statistical significance in our results.