Changes in Gun Laws and Their Impact on Lethal Violence:
A Causal Inference Study using a Difference-in-Differences Design.

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https://github.com/ChadDelany/causal_inference_castle_doctrine
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Introduction

Between 2000 and 2010, 21 states expanded the castle-doctrine statute to a new law called “Stand Your Ground”. Previously, lethal violence by a civilian was only allowed within their own home. In public, the “Duty to Retreat” was placed on the parties that felt threatened. With the Stand Your Ground law, civilians were now allowed to use lethal violence if they felt threatened. In addition, a civilian's use of force is considered a legal expression of feeling threatened. The law also removed any possibility for civil suits, which have a lower threshold for determining guilt. From an economic perspective, this lowers the cost of committing a homicide (Cunningham 2021). The intention behind this change in the law was to allow potential homicide victims to defend themselves and instead of being killed, allow the perpetrator of the potential homicide to be killed.

Since 2010 there are now, within the 50 states of the United States, currently 25 states that have Stand Your Ground laws, 8 states that have traditional Castle Doctrine laws, and 17 states that have explicit Duty to Retreat laws. Four additional states have adopted Stand Your Ground laws and 17 states have reacted by explicitly adopting Duty to Retreat laws. Understanding how this change in the law and its possible effect on lethal violence across the entire population is important for policymakers, gun reform advocates, and general citizens as we are all affected by gun laws and homicide rates. The question of the law's impact can be reduced to a data science analysis removing any moral, ethical, or political debates and simply determining a causal inference and what the actual impact of the law is over a population.

Problem

How did changing state laws regarding gun use impact lethal violence? What causal inference can be deduced from gun reform and lethal violence? The adoption of Stand Your Ground laws did not occur at one time period but with a staggered adoption rate, which allows for a complex difference-in-differences quasi-experimental design for inferring causality.

There are three possible outcomes from this change in the law with three interpretations for what those outcomes might be. The first possibility is that the Stand Your Ground law is working as intended. In this case, a situation that would have ended in the victim's death instead ends in the perpetrator's death. In this situation, one life is exchanged for another and the homicide rate would remain the same. The second possibility is that the Stand Your Ground Law with the removal of Duty to Retreat allows conflicts to escalate and situations that would not have ended in a homicide under previous laws now result in a homicide. In this situation, homicide rates would increase. The third possibility is that with the Stand Your Ground Law, rational criminals would perceive that the cost of commiting the crime is now higher, since they could be more readily killed, and the Stand Your Ground law would have a deterrent effect on crime. In this case, homicide rates would decrease. The primarily source of lethal violence in the United States is through the use of guns. A previous study (Lott and Mustard, 1997) determined that concealed-carry laws, which allow citizens to carry guns in public, had worked as a deterrent and reduced violence.

The causal inference analysis will conclude if the studied gun reform maintained previous homicide rates (true positive), was the cause of increased homicides (false positive), or the cause of decreased homicides (deterrent effect). By designing a multi-tiered difference-in-differences analysis, all known and unknown confounding factors will be removed so that actual causality can be inferred from only the change in gun laws. This analysis will be completed within one month.

Data Wrangling

The dataset used for this analysis is derived from the Uniform Crime Reporting Program that tracks 8 criminal stats across all 50 states since the 1920s - murder and non-negligent manslaughter, forcible rape, burglary, aggravated assault, larceny, motor vehicle theft, and arson. These statistics are converted into rates - incidents per 100,000 population. These rates are converted into log rates for use with linear regression models. The Uniform Crime Reporting Program is run by the Federal Bureau of Investigation. It is a voluntary program with local and state police agencies reporting and has a high response rate.

Exploratory Data Analysis

The goal of EDA is to explore the relationships between variables in the dataset and understand how the raw data behaves within the spatial and temporal window that the data encapsulate. Since the data are at the state level within the United States, the homicide rates were mapped for all 50 states and for each of the ten years. Figure 1 shows the year 2001 as a representative of all ten years explored. There does appear to be some regional variation with regard to homicide rates and restricting control groups to census regions might be beneficial in the analysis.

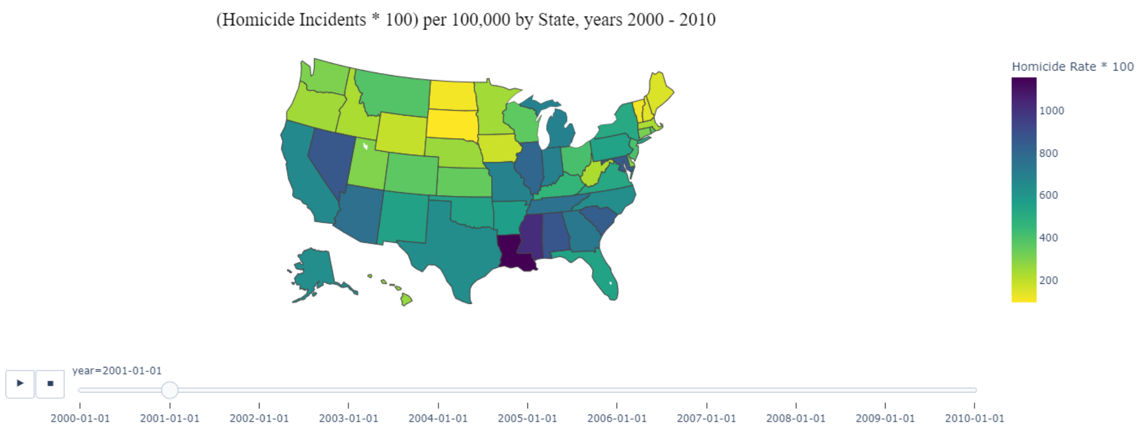

Figure 1. Homicide Rates per state in 2001.

While restricting control groups to census regions would remove any small spatial correlation, it would also decrease the sample size for the untreated states, i.e. the control group, and increase uncertainty in characterizing the control.

All of the state's homicide rates were also explored. In addition to looking at the raw data, the log homicide rate for each of the states that did adopt Stand Your Ground was graphed against the average log homicide rate for all states that never changed their castle doctrine. A line was plotted that indicates when the states changed their laws. From these graphs of the raw data, some states appear to have an increase in homicide rates associated with gun law changes, some states appear to have an associated decrease in homicide rates, and some states appear to have maintained previous trends. None of this raw data exploration determines any causality. As an example, Florida (figure 2) appears to have an associated increase in homicide rates while Texas (figure 3) appears to have maintained previous trends compared to the control.

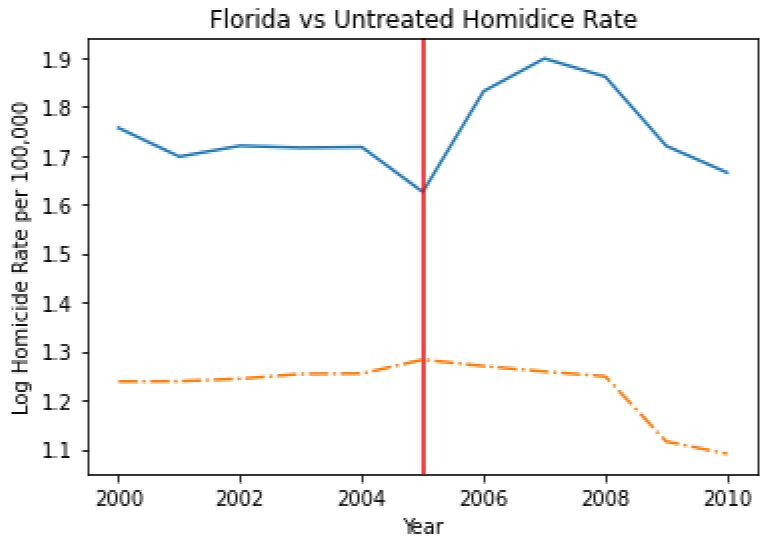

**Figure 2. Log Rate of Homicides in Florida compared to the control.
Adoption of Stand Your Ground in 2005.**

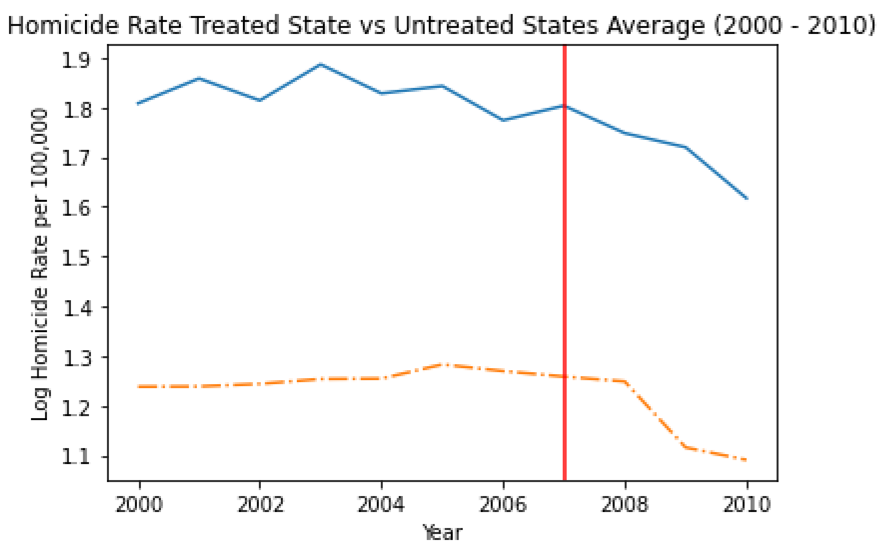

**Figure 3. Log Rate of Homicides in Texas compared to the control.
Adoption of Stand Your Ground in 2007.**

There does appear to be in some states a correlation from the changes in gun laws and also changes in homicide rate. But before the analysis, it can not be determined if this is causal or only correlated. At initial glance, there are also states that do not appear to have changes in homicide rates that occur at the same time as the changes in the gun law. The analysis will need to determine causality and significance.

Analysis

“[Difference-in-differences] has become the single most popular research design in the quantitative social sciences, and as such, it merits careful study by researchers everywhere.” (Cunningham 2021).

The classic difference-in-differences design was developed by John Snow in 1854 to determine the source of cholera. By having a treated group and an untreated group, two time periods, and a single treatment event, the difference first in time within each group and then the difference between the changes in the two groups, a causal inference can be made about the effects of the treatment event. By differencing the differences, unobserved confounding factors are controlled for. This classic and straightforward implementation of difference-in-differences is well understood. The underlying assumption to allow for making this inference is parallel-trends. The parallel-trends assumption assumes that the two groups would have continued in a similar trend if one of the groups had not experienced the treatment effect. By making this assumption, the counterfactual can be inferred for the treatment group. All causal inference hinges on being able to make a reasonable argument for what the counterfactual is, or what would have occurred if the group had not been treated. Then the causal effect can be determined by computing the difference between the counterfactual and the observed state of the treated group.

Inferring the counterfactual in the absence of randomized trials, has a number of methods. Difference-in-differences is the most popular and well established method for calculating the counterfactual and determining the causal relationship and magnitude of the treatment effect. Inherent within the difference-in-differences design and its underlying assumption of parallel-trends, is a control for all other confounding variables so that an explicit causal relationship between treatment and result can be inferred from the analysis. For this study, the treatment is the change in castle doctrine and the result is the homicide rate.

Most real-world data is not from randomized trials and does not have explicit causal determination. Most popular data science methods are only able to determine correlation but not causation. Most natural experiments do not fit easily into a simple structure of two similar groups, two time periods, and a single treatment. In order to apply the classic difference-in-differences design to more complex situations where there are more than two groups and differential timing in the applied treatment, the classic difference-in-differences is converted into a regression-based difference-in-differences design and from that is derived the regression-based twoway fixed effects model. They are so-called twoway fixed effects because they fix both the time effect and fix the unit or group effect. Following from the work of Cheng and Hoekstra [2013] applied to the change in castle doctrine, the twoway fixed effects with differential time regression equation is:

$$y_{it} = \alpha_0 + \delta D_{it} + X_{it} + \alpha_i + \alpha_t + \epsilon_{it}$$

Where D_{it} is the treatment parameter and X_{it} is a region-by-year fixed effect to account for regional variation.

Performing the twoway fixed effects with differential time regression, a clear causal picture arises. Figure 4 shows the overall effect of change in log homicide rate compared to when the castle doctrine changed. There is no causality or anticipation of changes to the law with respect to homicide rates before the adoption of the law. After the adoption of Stand Your Ground, homicide rates increased by 8%.

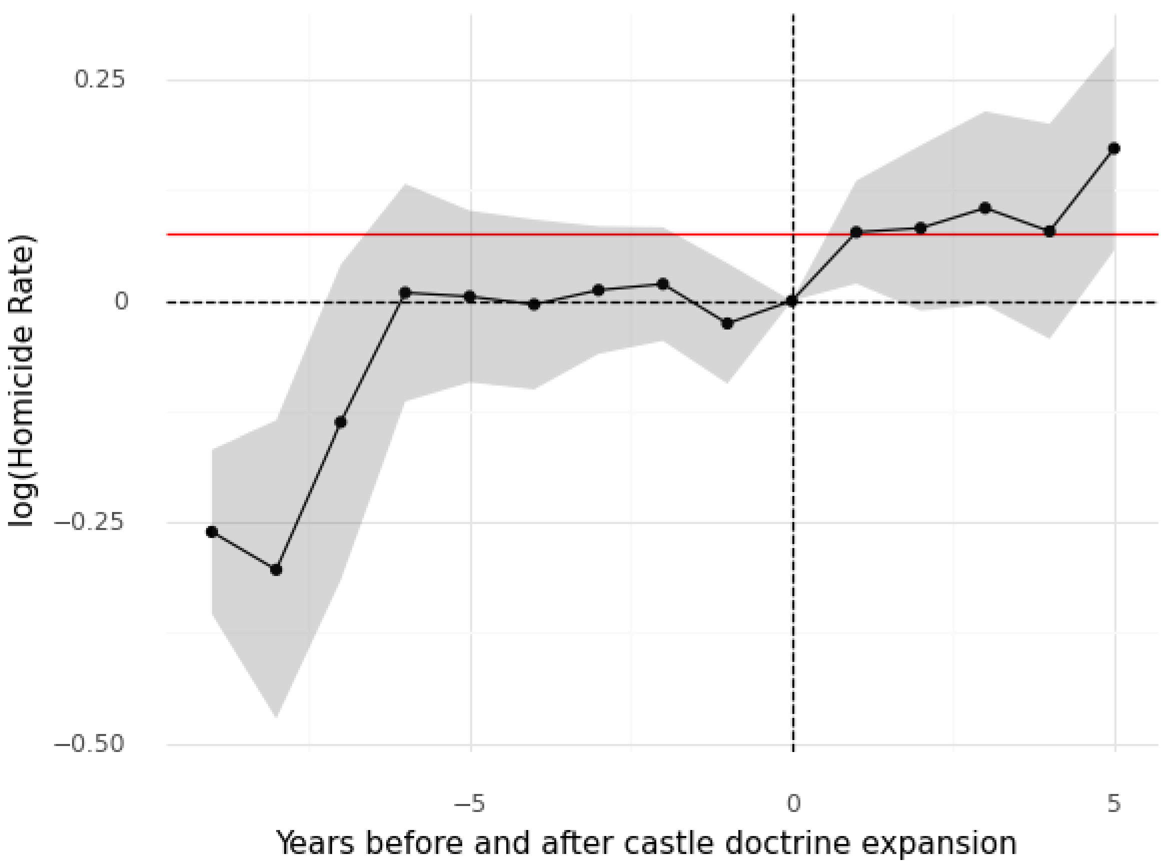

Figure 4. Increase in homicide rates causally linked to adoption of Stand Your Ground.

So, over the population of states that adopted the Stand Your Ground law between 2000 and 2010, there is a causally linked increase in the homicide rate of 8%. All other variables that cause a fluctuation in homicide rates have been controlled for. This increase is explicitly tied to the treatment event of the adoption of Stand Your Ground. While this analysis cannot explicitly comment on a single event (would Stand Your Ground in one instance generate a true positive or false positive result), it does show that over an entire population there is an 8% increase in situations that would have not resulted in a homicide under Duty to Retreat laws now escalating to resulting in a homicide under Stand Your Ground.

Next Steps

Very recently there has been active research regarding the difference-in-differences regression-based twoway fixed effects with differential timing analysis design. Goodman-Bacon (2021) has developed the Bacon Decomposition that shows underlying assumptions inherent in the regression derivation that compares treated groups with already-treated groups. In order for these analyses to be unbiased, the treatment effect cannot have any heterogeneity over time within its effect. This is usually not true in most real-world examples. The Bacon Decomposition is able to explicitly show the influence and magnitude of this biasing effect based on how heterogeneous the treatment effect is over time. In the case of the change in castle doctrine, the effect of increase in homicide rates is most likely larger since the biases shown in the Bacon Decomposition tend to decrease the effect measured by the twoway fixed effect with differential timing.

Since this is a very active research area within the statistics and econometric community of researchers, a number of tools are in the design and implementation stages. But there is no clear consensus on which tool is most appropriate to use for a given situation. Goodman-Bacon (2021) is able to characterize the biasing effect. Some very promising models are from Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Athey *et al* (2021). The matrix completion method seems most promising and utilizes machine learning to infer the counterfactual (Athey *et al*, 2021).

The next steps in this analysis would be to determine the bias using the Bacon Decomposition and use Matrix Completion and machine learning to infer the counterfactual. As well, since there is no consensus among the research community about which models are most appropriate for a given situation, several models could be used and results compared for a general understanding of the causal impact (Kumar 2023). Each model has its own set of underlying assumptions and it is unclear at this time which model is most appropriate. Currently, these models are not available in python.

Conclusion

While there are recently uncovered issues with the twoway fixed effects model, this does not change the causal inference of the model, only its potential significance with a likely increase in impact. With this analysis, under industry-wide accepted practices, there is a clear causal relationship between the adoption of Stand Your Ground and an increase in homicide rates, which is a false positive. Across the population, there is an 8% increase in situations that under Duty to Retreat would not have ended in homicide but under Stand Your Ground now escalate to homicide. This result is removed from any moral, ethical, or political debate. This is simply the measured impact of the law across this population.

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