Does the Castle Doctrine Affect Robberies

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Executive Summary

In this report, our team analyzed the effect of Stand Your Ground, a law which states that individuals have the right to use force outside of the home in self defense, on robberies in Florida. Our team performed a synthetic control approach to determine the effect of the Stand Your Ground Law on robberies in Florida, using data from the FBI. We found that after the Stand Your Ground legislation was passed in 2006 in Florida, the robberies per 100,000 state population increased in the first two years but dramatically decreased to normal level in 2010. It took about a year for this law to impact the number of robberies in Florida.

Background

The Castle Doctrine is a law which states that individuals have the right to use reasonable force, including deadly force, to protect themselves against an intruder in their home. Between 2000 and 2010, twenty-one states expanded the castle doctrine by permitting lethal force to be used outside the home in some places. This new expansion of the castle doctrine was called 'Stand your Ground.' The expansion meant that victims no longer had a duty to retreat in public places if they felt threatened. Instead, they could retaliate in lethal self-defense.

In the paper titled *Does Strengthening Self Defense Law Deter Crime or Escalate Violence*, authors Cheng Cheng and Mark Hoekstra used FBI data to analyze the impact of the expansion of the Castle Doctrine on Homicides in the United States using a difference-in-differences approach. In our analysis, we expanded Cheng and Hoekstra's analysis to discover how the implementation of Stand Your Ground affected robberies in Florida. We chose to analyze the effect of the Stand Your Ground Law in Florida because it was the first state to pass this law. According to the FBI data, the law passed in 2006 in Florida.

Overview of Data

We used the same data that Cheng and Hoekstra used from the fbi.gov website to analyze the affect of Stand Your Ground on robberies in Florida. The data is panel data, consisting of crime rates between the years of 2000 and 2010 for fifty states.

Our treatment group is Florida and our control group is the states which did not pass the Stand Your Ground Law until after 2010 (30 states). Our output variable is robbery per 100,000 state population. Each unit of observation is "robberies per 100,000 state population - year," meaning we have multiple observations for robberies per 100,00 state population over years of time.

Some other important features in our data include:

- Unemployment rate
- Poverty
- Percent of black male aged 15-24 and 25-44
- Percent of white male aged 15-24 and 25-44

Below you can see a snippet of what the data looks like.

```r
# Load libraries
library(tidyr)
library(dplyr)
library(ggplot2)
library(glmnet)
library(janitor)
library(Synth)
library(ggthemes)
library(patchwork)
library(causaldata)
library(scales)
```

```r
castle <- read.csv("G:/My Drive/Semester 2/Causal Inference/R Code/Data/castle_data_with

robbery <- castle %>% select('year', 'sid', 'state',
                             'robbery','post','unemployrt','poverty',
                             'blackm_15_24','whitem_15_24','blackm_25_44',
                             'whitem_25_44')

head(robbery)
```

```
##   year sid state  robbery post unemployrt  poverty blackm_15_24 whitem_15_24
## 1 2000   1       131.6136    0        4.1 14.70598     2.222243     4.694810
## 2 2001   1       128.3796    0        4.7 15.75020     2.249954     4.700201
## 3 2002   1       136.4233    0        5.4 15.55656     2.258261     4.685461
## 4 2003   1       137.6827    0        5.5 15.44780     2.292948     4.688166
## 5 2004   1       136.8653    0        5.1 16.25265     2.291327     4.661734
## 6 2005   1       145.1191    0        3.9 16.87298     2.312046     4.635865
```

```
##   blackm_25_44 whitem_25_44
## 1     3.471694    10.414437
## 2     3.440247    10.186382
## 3     3.403993     9.957734
## 4     3.383214     9.791410
## 5     3.358841     9.599033
## 6     3.357210     9.449511
```

Methods

Because we are interested in knowing the impact of passing the law in one state versus states where the law was not passed, we used a synthetic control approach rather than a difference-in-difference approach. We modeled Florida's trend before 2006 as a weighted average of control states before 2006, This weighted average will provide a good counter factual for comparison in the period after the law was passed. We can perform an empirical analysis between the actual robbery rate in Florida after 2006 and what the robbery rate would have looked like if the law were not passed.

We used the following equation to perform this analysis:

Robbery = B0 + B1xFlorida + B2xStandYourGround + B4xFloridaxStandYourGround + E

Threats to Causality

Before beginning our analysis, we must first establish causality by checking whether or not causal inference is valid for this data.

We first checked if robberies were correlated with the expansion of the Castle Doctrine. The code below shows that there is a relative correlation between the two.

```
cor(robbery$robbery, robbery$post)
```

```
## [1] 0.02926739
```

Next we checked if our data is free from endogeneity. We do believe that our data is free from endogeneity, but we have a few minor threats to causal inference such as

- Omitted Variable bias: confounding factors could also affect the number of robberies in Florida. Such omitted variables include gun laws, homelessness, income, and more.
- Measurement Error Bias: We believe that there is limited error in this data because the FBI is a reliable source, but we only have general information about robberies. We do not know further details such as who was involved in the crime.
- Simultaneity Bias: We want to ensure that although the Stand Your Ground law affects robberies, an increase in robberies does not correlate to the Stand Your Ground Law being passed. We do not believe that simultaneity bias is a threat to our causal inference.

Now that we have established that causal inference is valid for our data and addressed threats to causal inference, we can start our synthetic control analysis, beginning with our assumptions.

Assumptions

In order for our analysis to be valid, the following assumptions need to hold true:

- Parallel Trends: In order to check the impact of Stand Your Ground on robbery in Florida, we assumed and tested the trend to be parallel between Florida and the states where it was not passed.
- No Interference: We can also assume that if the law is passed in one state, it won't have any impact on the crime rate in other states and hence SUTVA holds true.

We also performed a placebo test to check an Anticipation Effect. An anticipation effect is where people see the natural experiment coming. To perform this test, we moved the year the law was passed a few years earlier than it really was passed.

We first prepare the data, creating a treatment column which indicates if the state was Florida or not and an intervention column, which indicates if the year was after 2006.

```
# list of control states
robbery_control_st <- robbery %>%
  group_by(sid) %>%
  summarise(post = max(post)) %>%
  filter(post == 0)

# control states
robbery_control <- robbery %>% filter(sid %in% robbery_control_st$sid)

# State 10 (Florida) as treatment
robbery_treat10 <- robbery %>% filter(sid == 10)

# combine treatment and control datasets
robbery10 <- rbind(robbery_treat10, robbery_control)
robbery10 = robbery10 %>% mutate(treatment = ifelse(sid=='10', 1, 0),
                                 intervention = ifelse(year>='2006', 1, 0))
```

Placebo Test:

```
data_placebo = robbery10 %>%
  mutate(after_placebo = ifelse(year > 2005, 1, 0))

did_basic_placebo = lm(robbery ~ treatment + after_placebo +
                         treatment*after_placebo,
```

```
                       data = data_placebo)
summary(did_basic_placebo)
```

```
##
## Call:
## lm(formula = robbery ~ treatment + after_placebo + treatment *
##     after_placebo, data = data_placebo)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -96.48 -39.84 -11.34  43.86 178.89
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              106.846      4.807  22.226  < 2e-16 ***
## treatment                 84.590     26.330   3.213  0.00145 **
## after_placebo             -3.715      7.130  -0.521  0.60266
## treatment:after_placebo   -5.849     39.054  -0.150  0.88105
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 63.41 on 326 degrees of freedom
## Multiple R-squared:  0.05256,    Adjusted R-squared:  0.04384
## F-statistic: 6.028 on 3 and 326 DF,  p-value: 0.0005248
```

We see that there is no effect because our interaction term, treatment:intervention, has a high p-value, meaning we fail to reject the null hypothesis that there is no effect of the Expand Your Ground Doctrine on robberies in Florida. Therefore, there is no placebo effect, and we can continue with our analysis.

Synthetic Control Analysis

Now we can perform our synthetic control analysis. We used the lasso method to assign fixed weights to our set of 30 control states where Stand Your Ground was not passed. In doing so, we will get a weighted average that closely resembles Florida's robbery activity before the Stand Your Ground was law was implemented, thus following the parallel trends assumption. This process will allow us to synthesize what Florida would have looked like after 2006 if the Stand Your Ground law was not passed.

We created our synthetic control group in the code below. We can see the weights that were assigned to each state to create the synthetic control group. The states that were given a positive weight are listed below.

```
### Synthetic Control using LASSO


# First we pivot the data from long to wide,
# to use other districts' time series as predictors.
robbery.wide <- robbery10 %>%
  pivot_wider(id_cols=c("year"),
              names_from=c("state"),
              values_from="robbery")
robbery.wide.train <- subset(robbery.wide,year<2006)



# We have many more predictors than time periods now,
# so we use LASSO for feature selection.
robbery.wide.train.lasso <- remove_empty(robbery.wide.train,
```

```r
                                              which=c("rows","cols"))
robbery.wide.train_mm <- model.matrix(`Florida`~.,
                                      robbery.wide.train.lasso)
lasso <- cv.glmnet(robbery.wide.train_mm,
                   robbery.wide.train$`Florida`,
                   standardize=TRUE,alpha=1,nfolds=5)
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations per
## fold
```

```r
## Weights
ests <- as.matrix(coef(lasso,lasso$lambda.1se))
ests
```

```
##                           s1
## (Intercept)    4325.41871240
## (Intercept)       0.00000000
## year             -2.09298788
## Arkansas          0.00000000
## California        0.00000000
## Colorado          0.00000000
## Connecticut       0.00000000
## Delaware          0.00000000
## Hawaii            0.01221104
## Idaho             0.00000000
## Illinois          0.00000000
## Iowa              0.00000000
## Maine             0.00000000
## Maryland          0.00000000
```

```
## Massachusetts       0.00000000
## Minnesota           0.00000000
## Nebraska            0.00000000
## Nevada              0.06488474
## `New Hampshire`     0.00000000
## `New Jersey`        0.06702647
## `New Mexico`        0.00000000
## `New York`          0.00000000
## `North Carolina`    0.00000000
## Oregon              0.00000000
## Pennsylvania        0.00000000
## `Rhode Island`      0.36583590
## Utah                0.00000000
## Vermont             0.00000000
## Virginia            0.00000000
## Washington          0.00000000
## Unknown1            0.00000000
## Unknown2            0.00000000
```

```
# Here are the non-zero control panels that lasso selected.
names(ests[ests!=0,])
```

```
## [1] "(Intercept)"    "year"            "Hawaii"          "Nevada"
## [5] "`New Jersey`"   "`Rhode Island`"
```

We use these non-zero weights to create our synthetic control group.

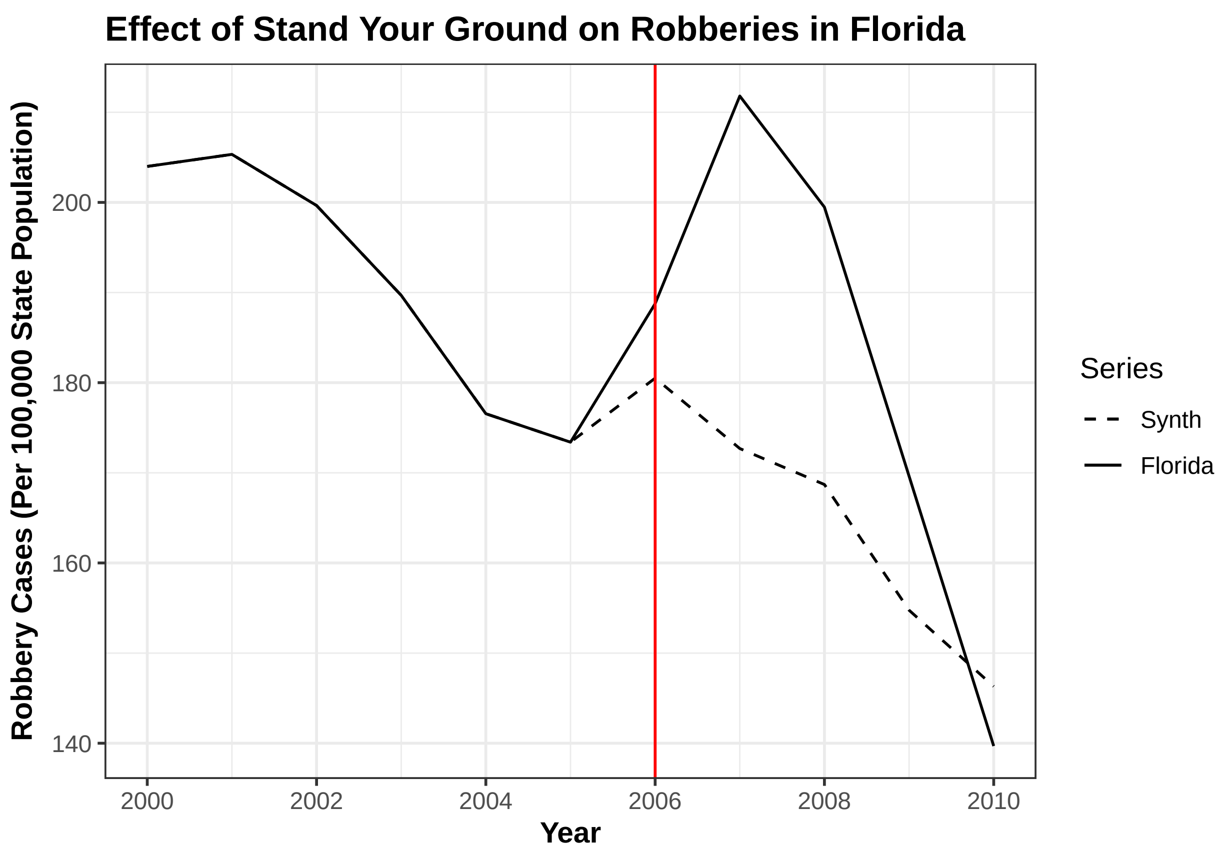
```
# We can use the resulting control districts to create
# our 'synthetic control'.
fml.rhs <- paste(c(names(ests[ests!=0,]))[2:length(names(ests[ests!=0,]))],
```

```r
                 collapse="+")
fml <- as.formula(paste("`Florida`~",fml.rhs))
synth <- lm(data=robbery.wide.train,formula=fml)

# Last, we can synthesize the resulting control series
# into the post treatment period.
robbery.wide$synth <- predict(synth,newdata = robbery.wide)
```

Finally, we graph our synthetic control and treatment group (Florida), to see the effect of the Castle Doctrine after the Stand Your Ground Law was passed in Florida.

```r
ggplot(data=robbery.wide,aes(y=synth,x=year,linetype="dashed")) +
  geom_line() +
  geom_line(aes(y=`Florida`,x=year,linetype="solid")) +
  geom_vline(xintercept=2006,color="red") +
  xlab(expression(bold(paste("Year")))) +
  ylab(expression(bold(paste("Robbery Cases (Per 100,000 State Population)")))) +
  scale_linetype_manual(name="Series",
                        values=c("dashed","solid"),
                        labels=c("Synth","Florida"))+
  ggtitle(expression(bold(paste("Effect of Stand Your Ground on Robberies in Florida")))
  scale_x_continuous(breaks = seq(2000, 2010, 2)) +
  theme_bw()
```



Results & Conclusions

Based on the graph above, there is a slight increase in robbery count between 2005 and 2007 and then a sharp decrease for treatment. This is possibly due to a Primacy effect which essentially accounts for the lag in the impact of passing a law. Although robbery increased for the first 2 years after Stand Your Ground was implemented in 2006, robberies decreased more dramatically after 2007. In 2010, the robbery rates go back to a relatively low level.

The synthetic control method gives us the value of the Average Treatment on the Treated, which means that we cannot generalize the effect of Stand Your Ground on other states. We can only understand how robberies changed in Florida after the law was passed.

We estimate this Average Treatment on the Treated by calculating the difference-in-difference value.

```r
# synthetic pre and post treatment
robbery.wide$synth
```

```
##        1        2        3        4        5        6        7        8
## 203.9897 205.3277 199.6549 189.6903 176.5549 173.3984 180.4991 172.6932
##        9       10       11
## 168.6987 154.7592 146.3027
```

```r
# robberies in Florida pre and post treatment
robbery %>% filter(sid==10) %>% select('year', 'robbery')
```

```
##    year  robbery
## 1  2000 203.9897
## 2  2001 205.3277
## 3  2002 199.6549
## 4  2003 189.6902
## 5  2004 176.5549
## 6  2005 173.3984
## 7  2006 188.7629
## 8  2007 211.8021
## 9  2008 199.4740
## 10 2009 169.6317
## 11 2010 139.6884
```

```r
# pre treatment difference between Florida and synthetic control
pre_trt = ((203.9897 - 203.9897) +
             (205.3277 - 205.3277) +
             (199.6549 - 199.6549) +
             (189.6902 - 189.6903) +
```

```r
             (176.5549 - 176.5549) +
             (173.3984 - 173.3984))/6
# post-treatment difference between Florida and synthetic control
post_trt = ((188.7629 - 180.4991) +
              (211.8021 - 172.6932) +
              (199.4740 - 168.6987) +
              (169.6317 -  154.7592))/4
# take difference of difference
post_trt - pre_trt
```

```
## [1] 23.25514
```

We obtain a value of 23.25, meaning that the average treatment on the treated is 23.25. This means that there was an average increase in robberies after the Stand Your Ground Law was implemented. However, when we look at the graph above, we see that there was a decrease in robberies in the long run. Florida should continue to use the synthetic control method in the future to determine if new policies that Florida implements affect crimes in Florida.

Limitations

Our limitations in this analysis are mainly due to the data source. Since we are not able to design and conduct experiments, we can only use observation data in limited years with limited variables.

- We have limited years: in our analysis, we saw a decreasing trend from 2005 to 2010. But it is possible that the robbery rates will go back to a high level after 2010. So if we had data after 2010, we would check if the trend continues to decrease to be sure that robberies do decrease after Stand Your Ground.
- We have limited variables: we construct the parallel trend based on other 4 states

for Florida as a good counterfactual. But we only use 6 variables in our analysis: unemployment rate, poverty, percentages of black and white males in different age groups. If we had more granular data, we would look into other variables to make more solid conclusions. Other variables that we would look into include location and time of crime, education, income, and homelessness.

Although we had a few limitations to our analysis, we were able to conclude that the Stand Your Ground Law did in fact affect robberies in Florida by causing robberies to decrease in the long run.