Untitled

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Lott and Mustard Replication Excercise

Introduction

For years the relationship between crime and gun laws has been a topic of significant contention in the United States. Some argue that restricting gun ownership will deter gun violence, while those on the other end of the aisle believe in quite the opposite. Researchers John Lott and David Mustard aimed to clear up this argument in their paper, "Crime, Deterrence, and Right-to-Carry Concealed Handguns." The authors attempt to tackle this problem by analyzing the effects of concealed carry laws on various crime rates using econometric models aimed at inferring causality. The authors conclude that when states give their citizens the right to carry a concealed firearm, violent crime rates decline without a significant increase in accidental gun deaths. Their findings are quite intriguing, but were their methods sound?

The goal of the analysis below will be to assess the models used by Lott and Mustard and see how they stack up to contemporary causal inference methods. We will look at the same data used by the researchers and first attempt to replicate their results. We will then used other predictive models to see if we see the same effects depicted by the researchers. Ultimately, we will assess what methods are the most effective in determining causal effects and highlight the implications of using a faulty model.

Background and Economic Theory

Data

Empircal Model and Estimation

The first model we will look at will be similar to the model originally used by Lott & Mustard in their paper. This model, 'Twoway Fixed Effects,' is a type of difference-in-difference design where we compare our observations to a fixed effect to identify whether a treated group has a different trend than a control group.

```
baconator = foreach(y = 1:len_, .combine = rbind) %do% {
  y_var = y_vars[y]

  bacon_name = paste("bacon", y_var, sep="_")
  fname_bacon = paste0(bacon_name, ".RDs")

  load(file.path(here(), "output", "models", fname_bacon))
```

Table 1: Table 1

State Name	Year Treated
Alabama	Treated Entire Period
Connecticut	Treated Entire Period
New Hampshire	Treated Entire Period
North Dakota	Treated Entire Period
South Dakota	Treated Entire Period
Vermont	Treated Entire Period
Washington	Treated Entire Period
Indiana	1981
Maine	1986
Florida	1988
Virginia	1989
Georgia	1990
Pennsylvania	1990
West Virginia	1990
Idaho	1991
Mississippi	1991
Oregon	1991
Montana	1992

Table 2: Summary Statistics

	Mean	Sd
Arest Rates - Violent Crime	41.09	22.20
Property Crime	16.92	4.68
Murder	91.30	55.94
Rape	41.02	17.39
Robbery	31.46	13.59
Burglary	13.80	4.57
Larceny	18.54	5.20
Auto Theft	22.35	37.61
Crime Rates - Violent Crime	483.93	318.94
Property Crime	4618.34	1210.46
Murder	7.77	6.88
Rape	33.98	15.07
Agravated Assault	278.76	159.65
Robbery	163.42	176.25
Auto Theft	410.30	231.15
Burglary	1239.34	417.76
Larceny	2968.71	751.02

```
  estimates = c(y_var, bacon_model[1,])
  estimates2 = c(y_var, bacon_model[3,])

  rbind(estimates, estimates2)
} %>%
  data.frame()

colnames(baconator) = c("Treated_Variable_(Log)", "Type", "Average_Estimate", "Weight")
rownames(baconator) = NULL

baconator = baconator %>%
  mutate(`Treated_Variable_(Log)` = ifelse(row_number()%%2 == 0, "", c("Rate of Violent Crime", "Murder


baconator_table = stargazer(baconator, type = "latex", summary = FALSE, rownames = FALSE)
```

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Tue, May 03, 2022 - 7:43:14 PM

Table 3

Treated_Variable_(Log)	Type	Average_Estimate	Weight
Rate of Violent Crime	Earlier vs Later Treated	0.0756132016382009	0.0683810328440173
	Later vs Earlier Treated	-0.0764501212365374	0.0233921216601542
Aggravated Assault Rate	Earlier vs Later Treated	-0.0105167537467737	0.0683810328440173
	Later vs Earlier Treated	0.00644375588610763	0.0233921216601542
Auto Crime Rate	Earlier vs Later Treated	0.0797367265339	0.0683810328440173
	Later vs Earlier Treated	0.00178777888242826	0.0233921216601542
Rape Rate	Earlier vs Later Treated	-0.0386438929436293	0.0683810328440173
	Later vs Earlier Treated	-0.0824341935444091	0.0233921216601542
Larceny Rate	Earlier vs Later Treated	0.116447300047853	0.0683810328440173
	Later vs Earlier Treated	-0.147173835565708	0.0233921216601542
Murder Rate	Earlier vs Later Treated	0.107751494707303	0.0683810328440173
	Later vs Earlier Treated	0.0895489195486503	0.0233921216601542
Burglary Rate	Earlier vs Later Treated	-0.0339653903210942	0.0683810328440173
	Later vs Earlier Treated	-0.0556312936611569	0.0233921216601542
Property Crime Rate	Earlier vs Later Treated	-0.00608332271323662	0.0683810328440173
	Later vs Earlier Treated	0.0207703124120926	0.0233921216601542
Robbery Rate	Earlier vs Later Treated	0.0831263198666238	0.0683810328440173
	Later vs Earlier Treated	0.0868025057315588	0.0233921216601542

```
baconator_table
```

[1] " "
[2] "% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com" [3] "% Date and time: Tue, May 03, 2022 - 7:43:14 PM"
[4] "\begin{table}[!htbp] \centering"
[5] " \caption{} "
[6] " \label{} "
[7] "\begin{tabular}{@\\extracolsep{5pt} cccc}"
[8] "\\[-1.8ex]\hline"

[9] “\hline \\[-1.8ex]”
[10] “Treated\ *Variable*\(Log) & Type & Average_Estimate & Weight \\ ”
[11] “\hline \\[-1.8ex]”
[12] “Rate of Violent Crime & Earlier vs Later Treated & 0.0756132016382009 & 0.0683810328440173 \\”
[13] ” & Later vs Earlier Treated & -0.0764501212365374 & 0.0233921216601542 \\ ”
[14] “Aggravated Assault Rate & Earlier vs Later Treated & -0.0105167537467737 & 0.0683810328440173 \\”
[15] ” & Later vs Earlier Treated & 0.00644375588610763 & 0.0233921216601542 \\ ”
[16] “Auto Crime Rate & Earlier vs Later Treated & 0.0797367265339 & 0.0683810328440173 \\”
[17] ” & Later vs Earlier Treated & 0.00178777888242826 & 0.0233921216601542 \\ ”
[18] “Rape Rate & Earlier vs Later Treated & -0.0386438929436293 & 0.0683810328440173 \\”
[19] ” & Later vs Earlier Treated & -0.0824341935444091 & 0.0233921216601542 \\ ”
[20] “Larceny Rate & Earlier vs Later Treated & 0.116447300047853 & 0.0683810328440173 \\”
[21] ” & Later vs Earlier Treated & -0.147173835565708 & 0.0233921216601542 \\ ”
[22] “Murder Rate & Earlier vs Later Treated & 0.107751494707303 & 0.0683810328440173 \\”
[23] ” & Later vs Earlier Treated & 0.0895489195486503 & 0.0233921216601542 \\ ”
[24] “Burglary Rate & Earlier vs Later Treated & -0.0339653903210942 & 0.0683810328440173 \\”
[25] ” & Later vs Earlier Treated & -0.0556312936611569 & 0.0233921216601542 \\ ”
[26] “Property Crime Rate & Earlier vs Later Treated & -0.00608332271323662 & 0.0683810328440173 \\”
[27] ” & Later vs Earlier Treated & 0.0207703124120926 & 0.0233921216601542 \\ ”
[28] “Robbery Rate & Earlier vs Later Treated & 0.0831263198666238 & 0.0683810328440173 \\”
[29] ” & Later vs Earlier Treated & 0.0868025057315588 & 0.0233921216601542 \\ ”
[30] “\hline \\[-1.8ex]”
[31] “\end{tabular}”
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