Lott and Mustard Replication Assignment

Elliott Metzler

5/4/2022

1 Introduction

This paper explores the findings of Lott and Mustard's 1997 paper titled "Crime, Deterrence, and Right-to-Carry Concealed Handguns". Specifically, we explore the original findings of the paper through a replication analysis using state level data, and extend the analysis to include more modern techniques of causal inference. Through application of modern techniques, we are able to better understand the original findings and ascertain their validity with more certainty.

In the original paper, the writers focused on applying a Fixed Effects model to their data. We replicate this model at the state level for comparison's sake. Additionally, we apply the Bacon Decomposition in order to more rigorously examine the underlying weights and pieces of the fixed effects coefficients produced by the original model. Third, we implement the Callaway and Sant'anna estimator. Last, we implement the Sun and Abraham event study.

The remainder of this paper is structured as follows. First, we discuss the background and economic theory of the original paper. Next, we discuss the data used for the replication and application of additional estimators. Third, we will present the four empirical models we implement on the data, discuss their purpose and implications, and present our results. Finally, we conclude with a summary and some implications of our study.

2 Background and Economic Theory

The original paper had a few key aims and implications. Principally, the authors were attempting to assess the impact of changes in concealed carry laws in the United States. Their study used data at the county level from the years 1977 to 1992 and included information on arrest rates, crime rates, demographic data, some economic data, and most importantly, an indicator variable for whether or not the county had a "shall issue" law. The "shall issue" law was useful for their purpose because these laws require officials to issue conceal carry gun permits to anyone who passes a basic screen for criminal record or history of significant mental illness. With this indicator variable, they posited that they could identify the causal impact of concealed carry on crime deterrence. We display the years in which each state that issued a shall issue law between 1977 and 1992 in Table 1.

Table 1: Shall Issue Law Rollout By State

State	Year
Alabama	1977
Connecticut	1977
New Hampshire	1977
North Dakota	1977
South Dakota	1977
Vermont	1977
Washington	1977
Indiana	1981
Maine	1986
Florida	1988
Virginia	1989
Georgia	1990
Pennsylvania	1990
West Virginia	1990
Idaho	1991
Mississippi	1991
Oregon	1991
Montana	1992

The author's main analytical approach was to use a two-way fixed effects model, accounting for as much variation between units (counties) as possible to isolate the impact of the shall issue laws on various crime rates. More specifically, the authors regressed the natural log of crime rate on a dummy for the shall issue law, the arrest rate for the same crime category in question, some economic-related variables (population per square mile, unemployment insurance, etc.), and demographic distribution variables. The crimes they evaluated included murder, rape, aggravated assault, robbery, property crime, burglary, larceny, and auto theft. Additionally, they combined murder, rape, aggravated assault, and robbery into a category "violent crime" and the other three into a category called "property crimes." For each of these crime categories, they estimated the two-way fixed effects model.

The author's main results from this approach show that shall issue laws are negatively related to each of the violent crimes. They also find that the shall issue laws are negatively associated with the property crimes.

Need to do for this section:

1. Add explanation of deterrence

3 Data

The data used for this replication and extension analysis is at the state level and includes each of the original variables required to replicate the main two-way fixed effects analysis performed by Lott and Mustard. Importantly, the data includes a row for each state for each year and each of the arrest rate, crime rate, economic, demographic, and shall issue indicator variables. We present summary statistics of the variables in Table 2 and Table 3.

Table 2: Main Variables Summary

Variable	N	Mean	Standard Deviation
Shalll	816	0.1912	0.3935
Violent Arrest Rate	802	41.0906	22.2036
Property Arrest Rate	809	16.9180	4.6770
Murder Arrest Rate	806	91.2989	55.9428
Rape Arrest Rate	799	41.0231	17.3887
Assault Arrest Rate	809	44.6250	16.9783
Robery Arrest Rate	808	31.4581	13.5928
Burglary Arrest Rate	809	13.8044	4.5712
Larceny Arrest Rate	809	18.5372	5.1961
Autotheft Arrest Rate	808	22.3455	37.6114
Violent Crime Rate	816	483.9260	318.9425
Property Crime Rate	816	4618.3394	1210.4646
Murder Crime Rate	816	7.7683	6.8817
Rape Crime Rate	816	33.9818	15.0721
Assault Crime Rate	816	278.7551	159.6495
Robbery Crime Rate	816	163.4208	176.2506
Burglary Crime Rate	816	1239.3364	417.7576
Larceny Crime Rate	816	2968.7079	751.0234
Autotheft Crime Rate	816	410.2951	231.1537
Personal Income Rpc	816	9351.8205	4689.7012
Unemployment Insurance Rpc	816	50.0187	38.0808
Income Maintenance Rpc	816	115.2756	70.9528
Retirement Payments Rpc	816	1002.2257	546.4679
State Population	816	4646787.3419	5010349.8734
Density	816	355.9729	1408.2501

As shown in the first panel, we have the arrest rates and crime rates for each of the nine categories analyzed by the original authors. We also include real per capita values for personal income, unemployment insurance, income maintenance, retirement payments, state population, and density.

Table 3: Demographic Variables Summary

Variable	N	Mean	Standard Deviation
White Male 1019	816	0.0672	0.0151
Black Male 1019	816	0.0102	0.0112
Other Male 1019	816	0.0036	0.0076
White Female 1019	816	0.0641	0.0149
Black Female 1019	816	0.0101	0.0114
Other Female 1019	816	0.0035	0.0073
White Male 2029	816	0.0741	0.0120
Black Male 2029	816	0.0096	0.0104
Other Male 2029	816	0.0035	0.0072
White Female 2029	816	0.0726	0.0123
Black Female 2029	816	0.0104	0.0123
Other Female 2029	816	0.0036	0.0073
White Male 3039	816	0.0663	0.0118
Black Male 3039	816	0.0071	0.0082
Other Male 3039	816	0.0030	0.0066
White Female 3039	816	0.0658	0.0117
Black Female 3039	816	0.0081	0.0098
Other Female 3039	816	0.0033	0.0070
White Male 4049	816	0.0480	0.0091
Black Male 4049	816	0.0046	0.0056
Other Male 4049	816	0.0020	0.0047
White Female 4049	816	0.0483	0.0090
Black Female 4049	816	0.0055	0.0068
Other Female 4049	816	0.0022	0.0051
White Male 5064	816	0.0580	0.0105
Black Male 5064	816	0.0052	0.0069
Other Male 5064	816	0.0019	0.0061
White Female 5064	816	0.0625	0.0123
Black Female 5064	816	0.0065	0.0089
Other Female 5064	816	0.0023	0.0069
White Male 65o	816	0.0426	0.0114
Black Male 65o	816	0.0035	0.0048
Other Male 65o	816	0.0012	0.0046
White Female 65o	816	0.0623	0.0167
Black Female 65o	816	0.0054	0.0078
Other Female 65o	816	0.0014	0.0048

In the second panel we present summary statistics for the demographic variables in the data. These features are represented as proportions of the whole, and are broken down by gender, white or black or other, and age group.

4 Empirical Model and Estimation

This section presents each of the four methods applied to the data. First, we analyze using two-way fixed effects consistent with the authors original approach. Next, we implement the Bacon Decomposition. Finally, we implement the Callaway and Sant'anna estimator and the Sun and Abraham event study estimator.

4.1 Two way Fixed Effects

For the two way fixed effects model, we use a similar specification to the authors. For each category of crime, we run an individual two way fixed effects regression where the natural log of crime rate is the outcome, and the covariates include the shall issue dummy variable, the arrest rate associated with that crime, and the various control variables related to economic and demographic conditions. To account for unobservable differences between the states and years in the data, we use allow for fixed effects on these two variables. The key difference between our implementation and the author's original is that we use state level data as opposed to county level data. We present the key results of this analysis in the tables below.

As shown in the tables, we find a negative relationship between the shall issue dummy variable and the log of crime rate for all crime categories besides larceny. This result would indicate that implementation of a shall issue law should decrease crime rates for all categories besides larceny. The two largest coefficients (in terms of order of magnitude) appear in the regression for violent crime (column 1 of Table 4) and aggravated assault (column 2 of Table 5). Both of these coefficients are statistically significant at a 1 percent level, and suggest the largest change in crime rate for a change to a shall issue law setting.

Table 4: Replication of Table 3 Panel A : Fixed Effects Regressions

Dependent Variables:	violent_crime_rate_log	property_crime_rate_log	murder_crime_rate_log
Model:	(1)	(2)	(3)
Variables			
shalll	-0.0978***	-0.0072	-0.0507
	(0.0207)	(0.0137)	(0.0386)
Relevant_Arrest_Rate	-0.0003	-0.0020*	-0.0004**
	(0.0004)	(0.0011)	(0.0002)
Fixed-effects			
state	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	802	809	806
R^2	0.98146	0.96445	0.94792
Within R^2	0.47334	0.55426	0.31137

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Control variables ommited from table, though they were included in the analysis. Consistent with the original paper, control variables include: density, personal_income_rpc, unemployment_insurance_rpc, income_maintenance_rpc, retirement_payments_rpc, state_population, ppwm1019, ppbm1019, ppnm1019, ppwf1019, ppbf1019, ppnf1019, ppwm2029, ppbm2029, ppnm2029, ppwf2029, ppbf2029, ppnf2029, ppwm3039, ppbm3039, ppnm3039, ppwf3039, ppbf3039, ppnf3039, ppwm4049, ppbm4049, ppnm4049, ppwf4049, ppbf4049, ppnf4049, ppwm5064, ppbm5064, ppnm5064, ppwf5064, ppbf5064, ppnf5064, ppwm65o, ppbm65o, ppnm65o, ppwf65o, ppbf65o, ppnf65o.

Table 5: Replication of Table 3 Panel B : Fixed Effects Regressions

Dependent Variables:	rape_crime_rate_log	assault_crime_rate_log	robbery_crime_rate_log
Model:	(1)	(2)	(3)
Variables			
shalll	-0.0340	-0.1004^{***}	-0.0532^{*}
	(0.0272)	(0.0270)	(0.0311)
Relevant_Arrest_Rate	-0.0006	-0.0028^{***}	-0.0014^{*}
	(0.0004)	(0.0007)	(0.0008)
Fixed-effects			
state	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	799	809	808
R^2	0.94240	0.96632	0.98389
Within R^2	0.52351	0.51645	0.50471

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Control variables ommited from table, though they were included in the analysis. Consistent with the original paper, control variables include: density, personal_income_rpc, unemployment_insurance_rpc, income_maintenance_rpc, retirement_payments_rpc, state_population, ppwm1019, ppbm1019, ppnm1019, ppwf1019, ppbf1019, ppnf1019, ppwm2029, ppbm2029, ppnm2029, ppwf2029, ppbf2029, ppnf2029, ppwm3039, ppbm3039, ppnm3039, ppwf3039, ppbf3039, ppnf3039, ppwm4049, ppbm4049, ppnm4049, ppwf4049, ppbf4049, ppnf4049, ppwm5064, ppbm5064, ppnm5064, ppwf5064, ppbf5064, ppnf5064, ppwm65o, ppbm65o, ppnm65o, ppwf65o, ppbf65o, ppnf65o.

Table 6: Replication of Table 3 Panel C : Fixed Effects Regressions

Dependent Variables:	burglary_crime_rate_log	larceny_crime_rate_log	autotheft_crime_rate_log
Model:	(1)	(2)	(3)
Variables			
shalll	-0.0461**	0.0033	-0.0090
	(0.0190)	(0.0138)	(0.0283)
Relevant_Arrest_Rate	-0.0052***	-0.0011	-0.0003*
	(0.0015)	(0.0010)	(0.0002)
Fixed-effects			
state	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	809	809	808
R^2	0.95597	0.96600	0.96116
Within R^2	0.50429	0.54529	0.60312

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Control variables ommited from table, though they were included in the analysis. Consistent with the original paper, control variables include: density, personal_income_rpc, unemployment_insurance_rpc, income_maintenance_rpc, retirement_payments_rpc, state_population, ppwm1019, ppbm1019, ppnm1019, ppwf1019, ppbf1019, ppnf1019, ppwm2029, ppbm2029, ppnm2029, ppwf2029, ppbf2029, ppnf2029, ppwm3039, ppbm3039, ppnm3039, ppwf3039, ppbf3039, ppnf3039, ppwm4049, ppbm4049, ppnm4049, ppwf4049, ppbf4049, ppnf4049, ppwm5064, ppbm5064, ppnm5064, ppwf5064, ppbf5064, ppnf5064, ppwm65o, ppbm65o, ppnm65o, ppwf65o, ppbf65o, ppnf65o.

4.2 Bacon Decomposition

- Explain Analysis: Bacon Decomposition without controls
- Explain weights and DiD estimates
- Explain early to late 2x2s and late to early 2x2s. What is the problem with late to early?

Table 7: Bacon Decomposition: Assault Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.1487745	0.0683810	0.0079628
Later vs Always Treated	-0.0314314	0.1589397	0.0009728
Later vs Earlier Treated	-0.0174274	0.0233921	-0.0034427
Treated vs Untreated	-0.2207888	0.7492871	-0.1375213
Total TWFE	NaN	NaN	-0.1320284

Table 8: Bacon Decomposition: Autotheft Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.0887179	0.0683810	0.0056843
Later vs Always Treated	0.1885142	0.1589397	0.0336117
Later vs Earlier Treated	0.0994063	0.0233921	0.0020305
Treated vs Untreated	0.0086094	0.7492871	0.0262756
Total TWFE	NaN	NaN	0.0676020

Table 9: Bacon Decomposition: Burglary Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	-0.0146061	0.0683810	-0.0023226
Later vs Always Treated	0.0169005	0.1589397	0.0048413
Later vs Earlier Treated	-0.0157802	0.0233921	-0.0013013
Treated vs Untreated	-0.0068820	0.7492871	0.0064291
Total TWFE	NaN	NaN	0.0076465

Table 10: Bacon Decomposition: Larceny Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.0088734	0.0683810	-0.0004160
Later vs Always Treated	0.0477985	0.1589397	0.0080003
Later vs Earlier Treated	0.0616798	0.0233921	0.0004859
Treated vs Untreated	0.0346292	0.7492871	0.0280699
Total TWFE	NaN	NaN	0.0361400

Table 11: Bacon Decomposition: Rape Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	-0.0264193	0.0683810	-0.0026425
Later vs Always Treated	-0.2001560	0.1589397	-0.0305273
Later vs Earlier Treated	-0.0106483	0.0233921	-0.0019283
Treated vs Untreated	-0.0030557	0.7492871	0.0030423
Total TWFE	NaN	NaN	-0.0320558

Table 12: Bacon Decomposition: Robbery Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.0961047	0.0683810	0.0073682
Later vs Always Treated	0.0940074	0.1589397	0.0174822
Later vs Earlier Treated	0.1505417	0.0233921	0.0020947
Treated vs Untreated	-0.0263060	0.7492871	-0.0100514
Total TWFE	NaN	NaN	0.0168936

Table 13: Bacon Decomposition: Murder Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.0545024	0.0683810	0.0054525
Later vs Always Treated	-0.0384771	0.1589397	-0.0012542
Later vs Earlier Treated	0.0188246	0.0233921	0.0000418
Treated vs Untreated	-0.0848318	0.7492871	-0.0415959
Total TWFE	NaN	NaN	-0.0373558

Table 14: Bacon Decomposition: Property Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.0036098	0.0683810	-0.0007191
Later vs Always Treated	0.0504242	0.1589397	0.0085564
Later vs Earlier Treated	0.0490119	0.0233921	0.0001507
Treated vs Untreated	0.0238073	0.7492871	0.0210569
Total TWFE	NaN	NaN	0.0290449

Table 15: Bacon Decomposition: Violent Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.1000224	0.0683810	0.0051705
Later vs Always Treated	-0.0596393	0.1589397	-0.0044690
Later vs Earlier Treated	0.0208665	0.0233921	-0.0017883
Treated vs Untreated	-0.1422163	0.7492871	-0.0839315
Total TWFE	NaN	NaN	-0.0850183

4.3 Callaway and Sant'anna

Prompt: Present a subsection in which you implement the Callaway and Sant'anna estimator. Describe the model with an equation and a description (short). Use the double robust specification. You will be analyzing each outcome and reporting the overall ATT. Do not report the group-level ATTs because many states simply do not have enough states per treatment date for the bootstrapping to provide accurate 95 percent confidence intervals. Use no more than 2 covariates – use your own judgment in selectin them. Report this in Table 4 and in your discussion compare what you found with the original findings. Are they similar? If not how do they differ?

4.4 Event Study (Sun and Abraham)

Prompt: Finally, implement the Sun and Abraham event study. While you can estimate Callaway and Sant'anna event studies, I would like to use Sun and Abraham. Explain the interaction weighted estimator and show a figure of each crime. Do pretrends appear to hold? How confident do you feel then that parallel trends holds for each outcome. This should only be presented as a Figure, not a table.

5 Conclusion

Prompt: What do you think you learned from this exercise? Feel free to discuss as little or as much as you want. I am just interested in your opinions. The purpose of this is merely to give you a nudge in considering how to interpret results and offer some commentary.