Lott and Mustard Replication

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I. Introduction

In 1997, John R. Lott and David B. Mustard published "Crime, Deterrence, and Right-to-Carry Concealed Handguns," an article that delineated the causality between citizens carrying concealed weapons and the violent crime rate. The orthodox method for causal inference prior to the 2000s was predicated about the fixed effects model, more particularly the panel fixed effects model. In the modern era, however, an amalgamation of research design methods have risen to prominence. The primary purpose of this study is to understand the contemporary methods of research design and scrutinize these studies with earlier analyses. It is significant, almost vital to have the specific understanding behind the historical changes of causality design as they include an additional factor for interpretation – treatment timing. For those interested in difference-in-difference methods, it is best to understand the initial evaluations to have a full grasp of status quo research desings..

II. Background and Economic Theory

"Crime, Deterrence, and Right-to-Carry Concealed Handguns" was written to dive further into the effects of concealed handgun permits on citizens and the crime rate. Gun violence is rampant across the United States, resulting in hundreds of thousands of gun encounters that can potentially result in fatalities. The literature surrounding gun control emphasizes that guns have been used defensively and have proved effective in preventing crime; thus, on net, these uses have saved lives. Lott and Mustard argue about the defensive nature of gun use and the reduced "hot burglary" (residents at home during burglary) percentage in the United States compared to Canada or Britain, correlative with the laxer restrictions on gun laws that America propagates. In fact, Lott and Mustard argue that the individual stories which use guns to defend themselves have given way for 31 states to adopt laws that give authorities the right to issue concealed-weapons permits to qualified applications (up from 9 states in 1986). More specifically, Lott and Mustard argue about the "shall issue" concealed handgun permit laws, which require permit requests be granted unless the individual has a criminal record or a history of significant mental illness.

Table 1 below indicates when 18 states face the "shall issue" concealed handgun permit laws and the introductory year of the respective law.

Table 1: Year of States that passed RTC laws

state	group
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

And thus, the question must be asked: "Will allowed concealed handguns make it likely that otherwise law-abiding citizens will harm each other? Or will the threat of citizens carrying weapons primarily deter criminals?"

Lott and Mustard warrant their argument with anecdotal evidence from American burglars that fear potentially armed victims and have to "case" a house or avoid late-night burglaries. Logically, the argument is sound; weapons create fear, regardless of affiliation and thus, should theoretically prevent/deter crime. The analysis utilized a cross-sectional time series data for US counties in 1977 to 1992, ultimately finding that citizens with concealed carry deter violent crimes. There were two models deployed for analysis: a dummy variable model and a spline/trend model. The dummy model used a dummy variable for the passage of the "right-to-carry" (RTC) laws as 0 or 1. This tests whether the average crime level pre-passage is different that of post-passage on a statistical level. The spline model, on the other hand, measures the crime trend alteration following the adoption of the RTC laws. It utilizes a spline variable that indicates the number of years post-passage.

Lott and Mustard's estimates find that murder, rape, aggravated assault, and overall violent crime falls by 4-7% with passage of the RTC laws. They also find that property crime rates increased by about 2-9%, and they conclude that property crime rates are the substitute for violent crime given the prior argument that criminals want to reduce the risk that they would be shot. Therefore, gun-carrying laws conclusively deter violent crimes according to the original paper. In order to explore this claim further, we will utilize contemporary research methods and data post-1997.

III. Data

The data that I will be using to conduct the research design experiment is state-level data as opposed to the original study which employed county-level data. There are seven crime categories: murder, rape, aggravated assault, robberty, auto theft, burglary, larceny, violent crimes (summary of murder, rape, aggravated assault and robbery), and property crimes (theft, burglary, and larceny). It also includes the rates of these crimes, a "shall issue" dummy variable, state trend variables, state-based statistics, arrest rates for the crimes, and logs of the previous variables. The data incorporates the years from 1977 up to 2007. Table 2 portrays the summary statistics (replicated from the original Lott and Mustard paper) for the crime outcomes, inclusive of the added data and specific to the state-level interpretations.

Statistic	N	Mean	St. Dev.
ratmur	102	4.636	5.743
ratvio	102	281.060	300.158
rataga	102	168.189	153.928
ratpro	102	2,520.244	2,258.591
aovio	90	24.205	17.683
aomur	90	59.849	48.122
aopro	92	10.180	7.360
aorap	86	24.897	18.079
aorob	90	19.662	14.207
aoaga	92	27.785	19.386
aobur	92	8.533	5.861
aolar	92	11.155	8.142
aoaut	90	27.778	16.988

IV. Empirical Model and Estimation

To illustrate the discussion surrounding violent crime deterrence in Lott and Mustard's paper, we will emphasize two specific models to recreate.

a. Two-Way Fixed Effects

The TWFE model is the original model used by Lott and Mustard to conduct the research design analysis. Below, in the model, is the similar results that were initially estimated with the unique specification of an extended time period and state-level parameters. This difference-in-difference research method can be used to produce remarkable causality between an treatment and outcome. Remember that the TWFE model deployed here does not account for treatment timing and may be limited in analysis.

Lott and Mustard TWFE replication

	ATT
Assault	-0.1320300
Auto Theft	0.0676020
Burglary	0.0076465
Larceny	0.0361400
Murder	-0.0373560
Rape	-0.0320560
Robbery	0.0168940

b. Bacon Decomposition

A major critique of the TWFE model was cited by Andrew Goodman-Bacon in 2019, who uniquely constructed a technique for specifying treatment timing effects. Table 3 depicts the results of the Goodman-Bacon estimation modeling.

Table 3: Goodman-Bacon Decomposition

	treated	untreated	estimate	weight	type	weighted_estimate
3	1988	1977	0.0852421	0.0203295	Later vs Always Treated	0.0017329
4	1990	1977	0.1044291	0.0432464	Later vs Always Treated	0.0045162
5	1991	1977	0.0602288	0.0310487	Later vs Always Treated	0.0018700

Table 3: Goodman-Bacon Decomposition *(continued)*

	treated	untreated	estimate	weight	type	weighted_estimate
6	1981	1977	-0.0469482	0.0177421	Later vs Always Treated	-0.0008330
7	1986	1977	-0.0494952	0.0232865	Later vs Always Treated	-0.0011526
8	1992	1977	0.1104341	0.0055444	Later vs Always Treated	0.0006123
9	1989	1977	0.0706990	0.0177421	Later vs Always Treated	0.0012543
12	1988	99999	0.0735507	0.0958391	Treated vs Untreated	0.0070490
13	1990	99999	0.0924178	0.2038758	Treated vs Untreated	0.0188417
14	1991	99999	0.0374370	0.1463724	Treated vs Untreated	0.0054797
15	1981	99999	-0.0457186	0.0836414	Treated vs Untreated	-0.0038240
16	1986	99999	-0.0596925	0.1097793	Treated vs Untreated	-0.0065530
17	1992	99999	0.0869931	0.0261379	Treated vs Untreated	0.0022738
18	1989	99999	0.0574169	0.0836414	Treated vs Untreated	0.0048024
22	1990	1988	0.0858012	0.0009505	Later vs Earlier Treated	0.0000816
23	1991	1988	0.0833002	0.0009505	Later vs Earlier Treated	0.0000792
24	1981	1988	-0.0784070	0.0014785	Earlier vs Later Treated	-0.0001159
25	1986	1988	-0.1540037	0.0009505	Earlier vs Later Treated	-0.0001464
26	1992	1988	0.1869325	0.0002112	Later vs Earlier Treated	0.0000395
27	1989	1988	0.1305351	0.0002112	Later vs Earlier Treated	0.0000276
30	1988	1990	0.0277479	0.0034851	Earlier vs Later Treated	0.0000967
32	1991	1990	0.0107250	0.0009505	Later vs Earlier Treated	0.0000102
33	1981	1990	-0.1098499	0.0057028	Earlier vs Later Treated	-0.0006265
34	1986	1990	-0.1105860	0.0057028	Earlier vs Later Treated	-0.0006307
35	1992	1990	0.1395263	0.0003168	Later vs Earlier Treated	0.0000442
36	1989	1990	-0.0923686	0.0019009	Earlier vs Later Treated	-0.0001756
39	1988	1991	0.0854962	0.0052276	Earlier vs Later Treated	0.0004469
40	1990	1991	0.0766157	0.0061781	Earlier vs Later Treated	0.0004733
42	1981	1991	-0.1465195	0.0063365	Earlier vs Later Treated	-0.0009284
43	1986	1991	-0.1048123	0.0071285	Earlier vs Later Treated	-0.0007472
44	1992	1991	0.2439030	0.0001584	Later vs Earlier Treated	0.0000386
45	1989	1991	0.0557850	0.0038019	Earlier vs Later Treated	0.0002121
48	1988	1981	0.0256913	0.0018481	Later vs Earlier Treated	0.0000475
49	1990	1981	0.0154113	0.0042771	Later vs Earlier Treated	0.0000659
50	1991	1981	-0.0452445	0.0031682	Later vs Earlier Treated	-0.0001433
52	1986	1981	-0.0338089	0.0018481	Later vs Earlier Treated	-0.0000625
53	1992	1981	0.0245727	0.0005808	Later vs Earlier Treated	0.0000143
54	1989	1981	0.0083711	0.0016897	Later vs Earlier Treated	0.0000141
57	1988	1986	-0.0036494	0.0005280	Later vs Earlier Treated	-0.0000019
58	1990	1986	0.0532988	0.0019009	Later vs Earlier Treated	0.0001013
59	1991	1986	0.0131776	0.0015841	Later vs Earlier Treated	0.0000209
60	1981	1986	0.0162100	0.0010561	Earlier vs Later Treated	0.0000171
62	1992	1986	0.1262724	0.0003168	Later vs Earlier Treated	0.0000400
63	1989	1986	0.0848278	0.0006336	Later vs Earlier Treated	0.0000538
66	1988	1992	0.1681158	0.0023234	Earlier vs Later Treated	0.0003906
67	1990	1992	0.1821801	0.0041187	Earlier vs Later Treated	0.0007503
68	1991	1992	0.2279157	0.0022178	Earlier vs Later Treated	0.0005055
69	1981	1992	-0.0831708	0.0023234	Earlier vs Later Treated	-0.0001932
70	1986	1992	-0.0203829	0.0028514	Earlier vs Later Treated	-0.0000581
72	1989	1992	0.1698808	0.0019009	Earlier vs Later Treated	0.0003229

Table 3: Goodman-Bacon Decomposition *(continued)*

	treated	untreated	estimate	weight	type	weighted_estimate
75	1988	1989	0.1297972	0.0005808	Earlier vs Later Treated	0.0000754
76	1990	1989	-0.0613102	0.0004752	Later vs Earlier Treated	-0.0000291
77	1991	1989	0.0239645	0.0006336	Later vs Earlier Treated	0.0000152
78	1981	1989	-0.0340257	0.0016897	Earlier vs Later Treated	-0.0000575
79	1986	1989	-0.0192777	0.0014257	Earlier vs Later Treated	-0.0000275
80	1992	1989	0.1829779	0.0001584	Later vs Earlier Treated	0.0000290

The results that come from Goodman-Bacon's estimator compared to the original techniques are less than optimal for proving causality. The late to early 2x2s, more particularly the treatment and control groups that are treated at the ends of the different time periods, are problematic because they show the heterogeneity in times for the treatments (early as opposed to late) which also indicates that there an amalgamated impact from the treatment in the late group. Compared to the original TWFE model, this is imperative as selection bias exists in that decomposition method.

c. Callaway and Sant'anna

Another contemporary method of empirical analysis through TWFE was coined from Callaway and Sant'anna (2000) where there are two unique changes to the research design method. One change focused on removing the timing effects by grouping the treatments by cohorts (time periods that are shared between treatments group to control for treatment timing delivery relative to other cohorts). Another change utilizes a parametric estimator that permits historical information to be used for estimating the model's results. Below is the estimator:

$$ATT = E[(G/E[G] - (p(x)C/1 - p(x))/E[p(x)C/1 - p(x)]) * (Yt - Yg1)]$$

The model below uses the Callaway and Sant'anna estimator to produce the cohorts for the years when the "shall issue" laws were introduced and to accommodate for the timing effects.

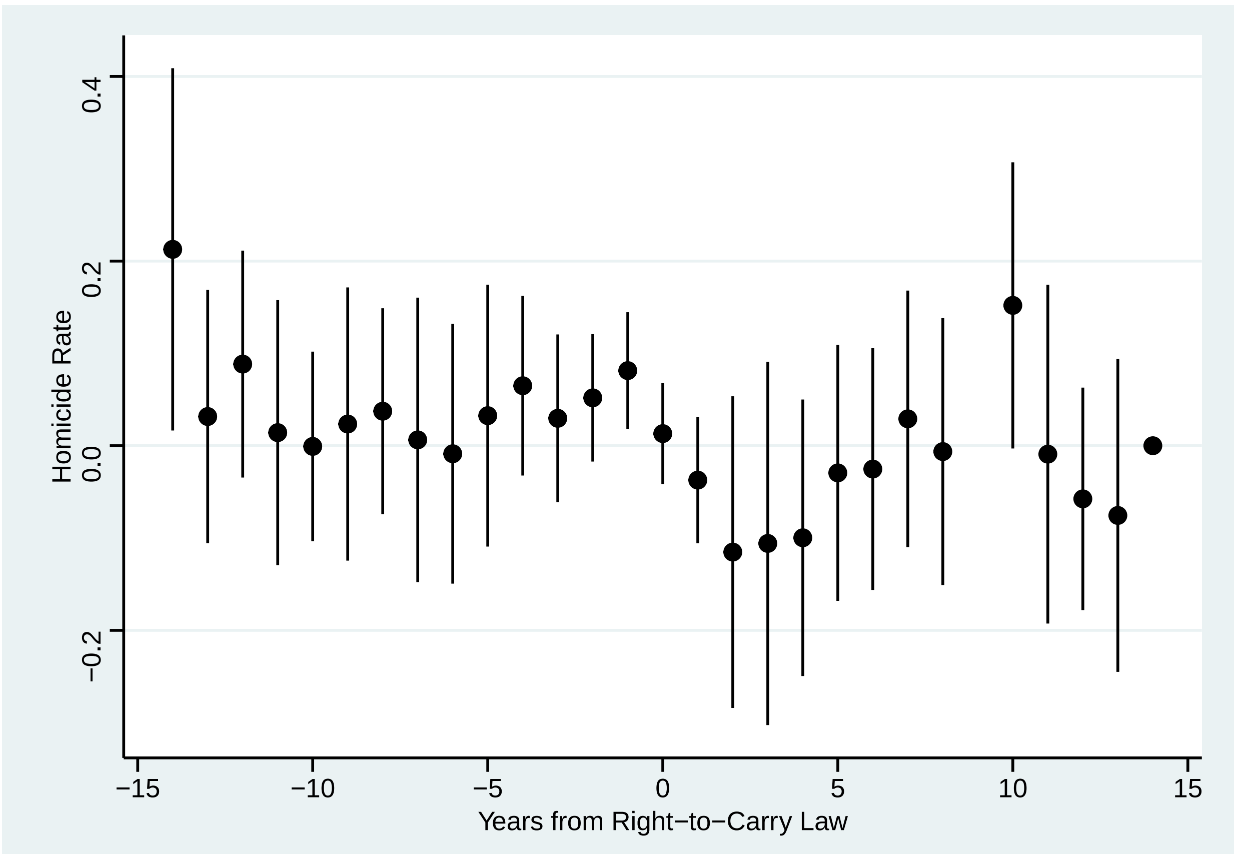
Table 4: Average Treatment Effect by Crime

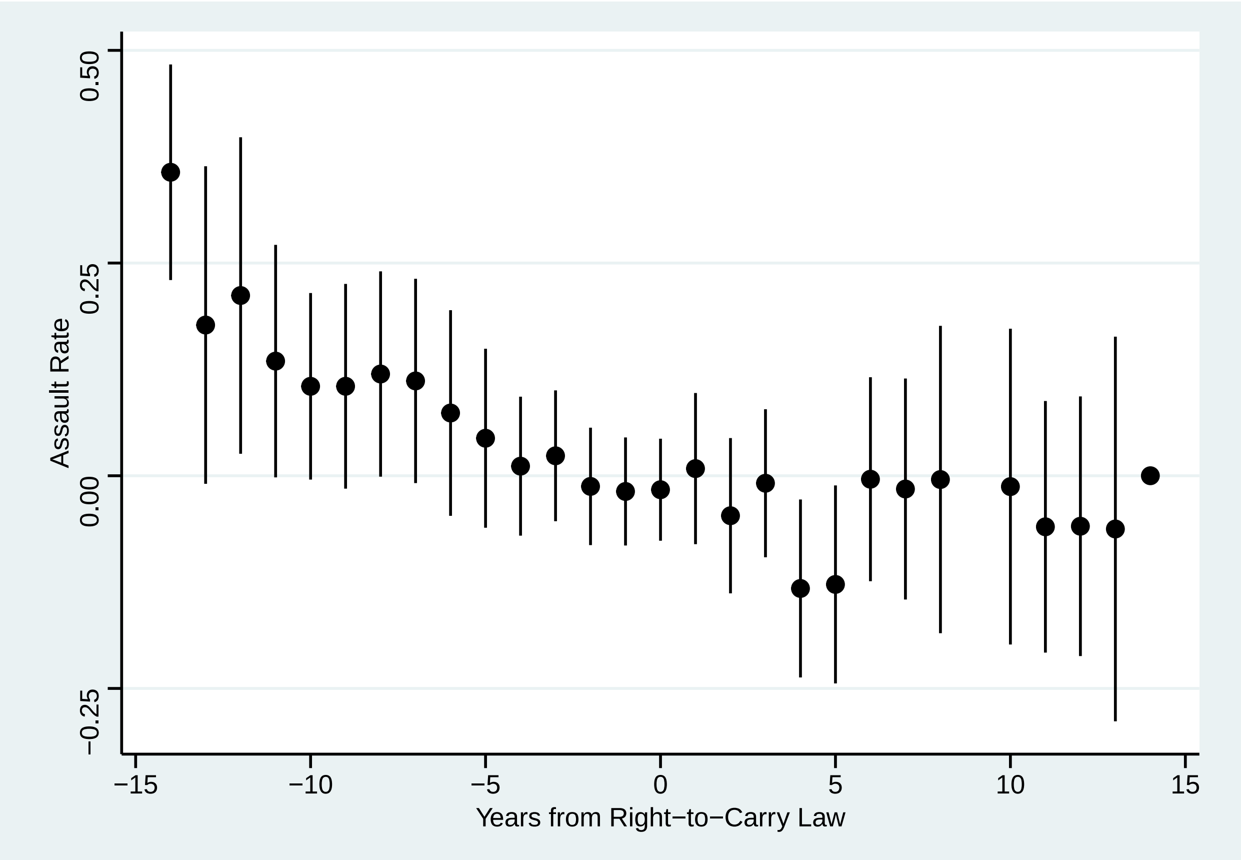
	ATT	STDE	Lower	Upper
Assault	-0.0635	0.0916	-0.2431	0.1160
Auto Theft	-0.0455	0.0407	-0.1252	0.0342
Burglary	-0.0509	0.0235	-0.0970	-0.0049
Larceny	-0.0221	0.0231	-0.0674	0.0231
Murder	-0.1079	0.0290	-0.1648	-0.0510
Rape	-0.0552	0.0600	-0.1728	0.0623
Robbery	-0.0770	0.0618	-0.1982	0.0441

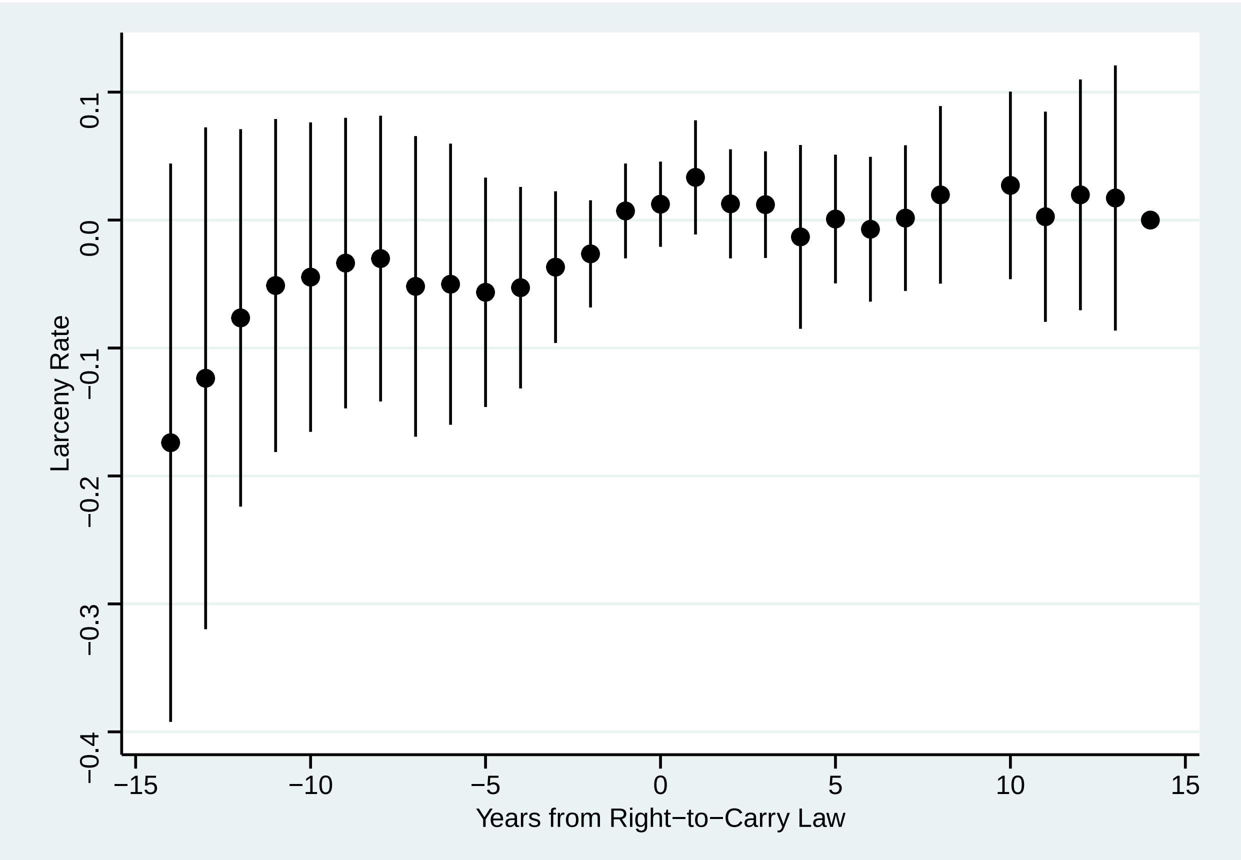
The results provided by the Callaway & Sant'anna model are different compared to the original Lott and Mustard paper that are smaller and less significant. This follows through with the hypothesis of timing treatments being a confounding factor in the previous results by the authors.

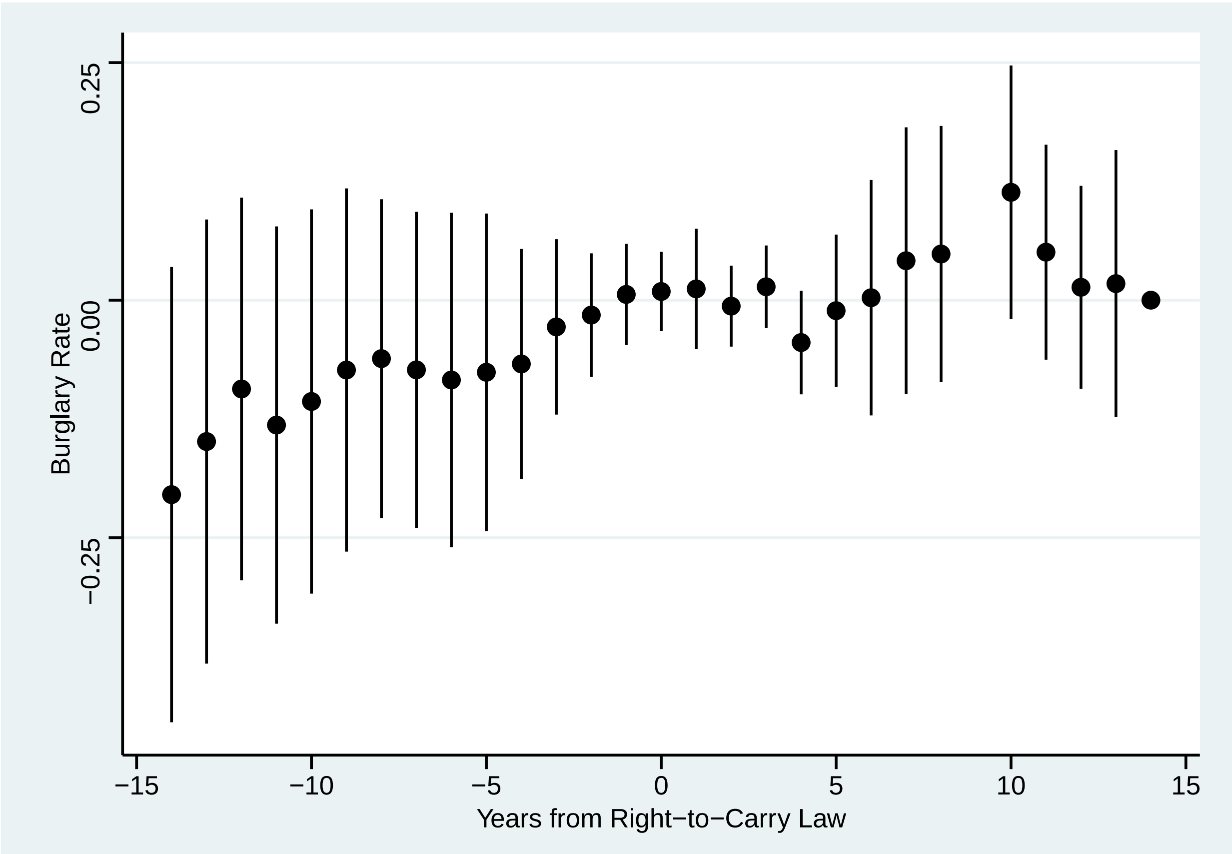
d. Event Study

One other method utilized in this analysis is the Sun & Abraham (2020) event study. Sun & Abraham use leads and lags into their model to account for the effects of differential timing of treatment and rectifying that trends are consistent over time. Another discrepancy from other contemporary methods is surrounding the interaction weighed estimator, which mixes the time distance from the treatment with the outcome; as aresult, compounding treatment over time is substantially reduced. Represented below are a series of figures that portray the controversial result: "shall issue" laws do not deter crimes. The figures also demonstrate pretrends appear to hold with the confidence intervals and that the treatment had a minimal, almost abyssmal impact on crime. The reductions and increases in specific crimes were already trending before the treatment was implemented. Out of all the various types of crime, auto theft had a relative impact from the treatment. It dropped a substantial amount a few lags after the treatment, which indicates that the pretrend did not hold. This was contradictory to the prior logic that Lott and Mustard (1997) stated where criminals may turn to auto-theft. Note each of the dependent variables are a logged form of the original crime.

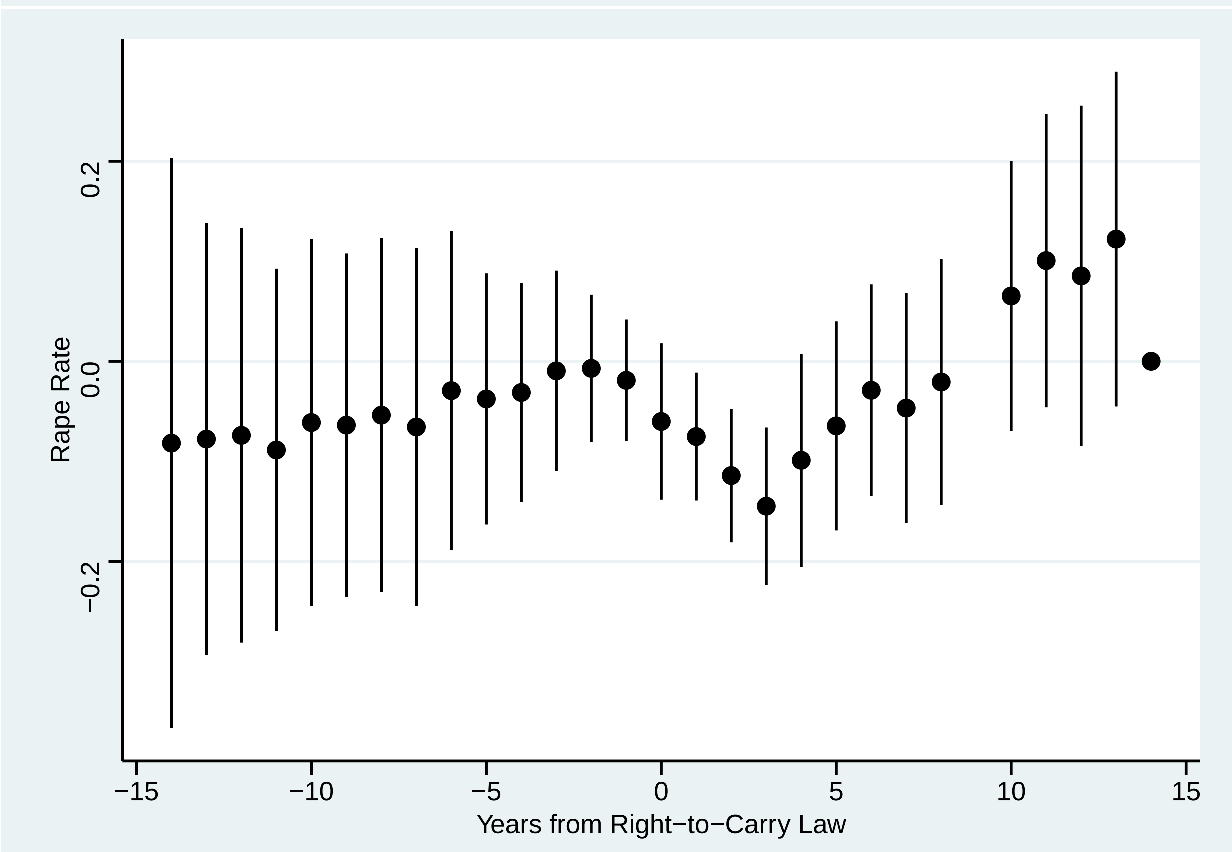



0.50
0.25
0.00
−0.25
Assault Rate
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law

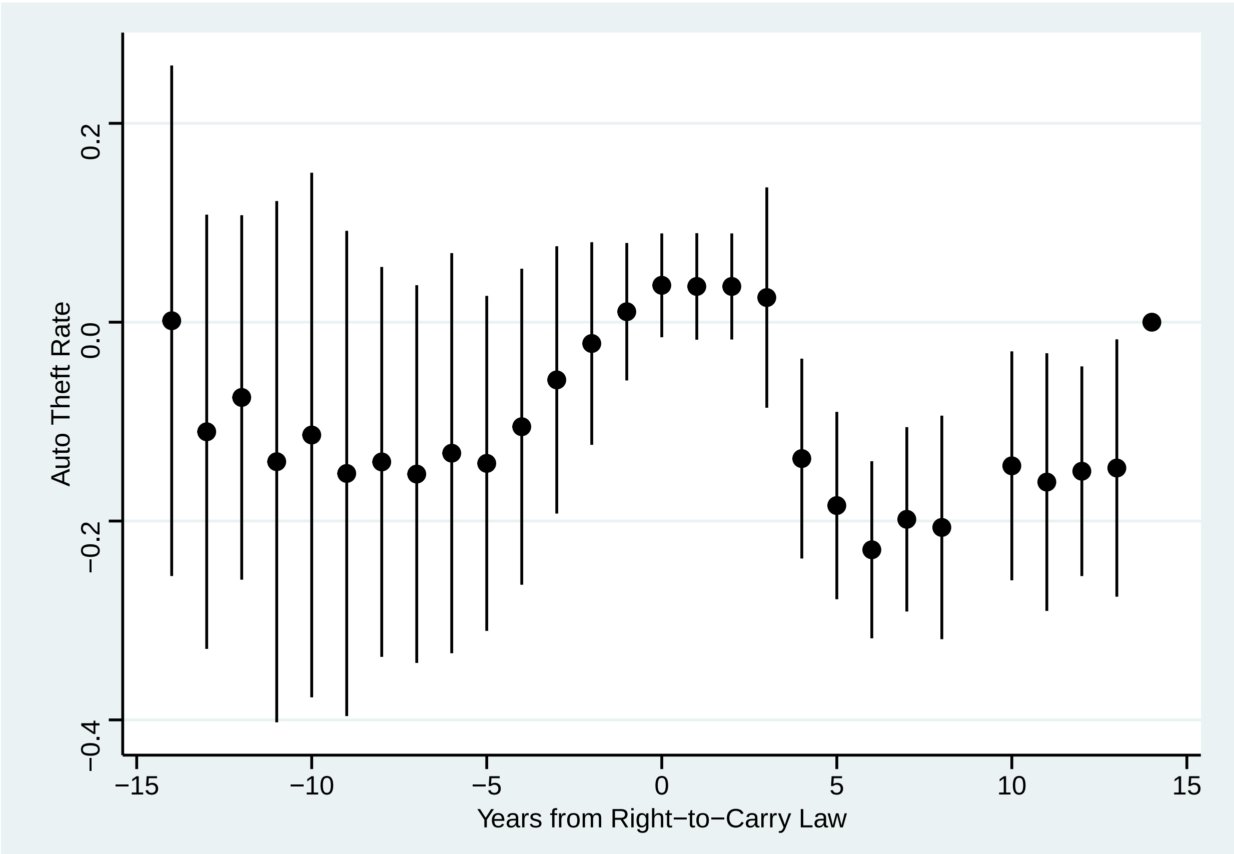

0.1
0.0
−0.1
−0.2
−0.3
−0.4
Larceny Rate
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law

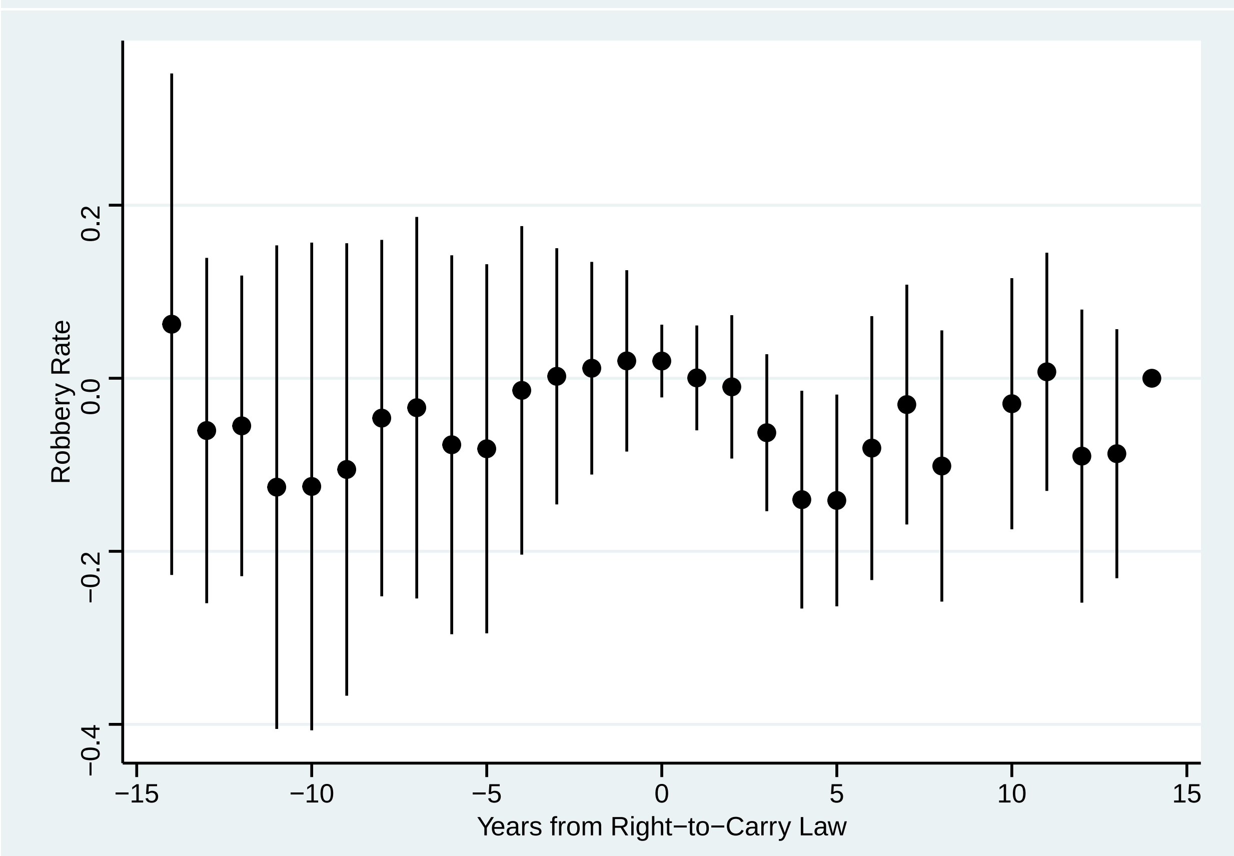


0.25
0.00
−0.25
Burglary Rate
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law



0.2
0.0
−0.2
Rape Rate
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law


Auto Theft Rate
0.2
0.0
−0.2
−0.4
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law


Robbery Rate
0.2
0.0
−0.2
−0.4
−15
−10
−5
0
5
10
15
Years from Right−to−Carry Law

V. Conclusion

This exercise has provided a more conceptual understanding of how TWFE is incredibly limited in regards to timing variations; more specifically how treatment effects are contingent due to timing. Contemporary methods are much more effective in detailing the missed nuances of older modeling techniques. The Bacon Decomposition method, Callaway and Sant'anna's DD estimator, Sun and Abraham's event study are all updated, unorthodox approaches comparative to the original TWFE model employed by Lott and Mustard. Furthermore, this analysis might tune more into reducing the credibility of Lott and Mustard's paper and the real world implications that follow such as the NRA utilizing the 1997 study as a warrant for improved gun rights. Generally speaking in the realm of causal inference, it is quite significant to have a deeper understanding of outdated methods and the status quo alternatives for quasi-experimental research design as minute details are relevant to designing an efficient, precise estimator for optimal conclusions.