Lott and Mustard Replication

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Introduction

Civilian gun ownership has always been a center of debate in U.S. politics, and scholars have been working on related issues throughout history. This topic is also what Lott and Mustard were trying to answer in their paper "Crime, Deterrence, and Right-to-Carry Concealed Handguns". They used the right-to-carry concealed gun law as the treatment to see its effect on 9 different types of crime, and the method they used was two-way fixed effect (TWFE). While TWFE is efficient and has been the default method for estimating difference-in-difference (DiD) with differential timing for years, it is not capable of handling treatments that are rolled out. Therefore, in this replication, we will try to solve two problems from the original Lott and Mustard paper. First, substitute county-level data with state-level data since the laws are implemented on a state level. Second, use alternative approaches that compensate for the downside of TWFE, the methods we would be using are proposed by Callaway & Sant'Anna, Goodman-Bacon, and Sun & Abraham.

Background and Economic Theory

In the original paper, the authors were trying to know by allowing concealed handguns, will the law-abiding citizen be more likely to hurt each other, or the threat of others carrying concealed weapons deter crime? In order to answer this question, they used the panel data for U.S counties from 1997 to 1992 and analyzed the data with two-way fixed effects model (TWFE). The outcome variable: crime they were using includes 9 different categories, the FBI crime reports include seven categories of crime: murder, rape, aggravated assault, robbery, auto theft, burglary, and larceny. Two additional summary categories were included: violent crimes (including murder, rape, aggravated assault, and robbery) and property crimes (including auto theft, burglary, and larceny). By using TWFE, they found out that allowing citizens to carry concealed weapons deters violent crimes and it appears to produce no increase in accidental deaths. Because of this law implementation rollout, our treatment is assigned with differential timing, meaning that a state might be part of the untreated group in one year and part of the treated group in another year. This treatment rollout is summarized in Table 1.

Table 1: Right-to-Carry Rollout

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

Data

In the panel data set, the right-to-carry law is coded 1 when the state has implemented the law, and 0 otherwise. While the authors used county-level data in the original paper, here we will be using state-level data since the right-to-carry laws are implemented at a state level, and it is noted that the county-level data have substantial measurement errors.

The below table (table 2) shows the average arrest rate and its standard deviation for each type of crime, this number is calculated by using the average across states and years. We can see that Murder has the highest arrest rate at 91.3% followed by Aggravated Assault, Violent Crime, and Rape at around 40%, while auto theft is at the lowest at 13%. From this statistic, we can understand the focus of law enforcement is mainly on felony and serious crimes.

Table 2: Arrest Statistics

	Mean	Sd
Violent Crime	41.09	22.20
Property Crime	16.92	4.68
Murder	91.30	55.94
Rape	41.02	17.39
Aggravated Assault	44.62	16.98
Robbery	31.46	13.59
Auto Theft	13.80	4.57
Burglary	18.54	5.20
Larceny	22.35	37.61

Table 3 here shows the average and standard deviation of the frequency of the crime outcomes per 100,000 people by using the average across states and years. We can see that the frequency decreases when the egregiousness of the crime increases, with murder and rape being the most infrequent crimes. There might be two possible reasons for this outcome, one is that people are just less likely to commit this kind of crime, and the second is that the high arrest rate as shown in table 2 serves as a form of deterrence to these egregious crimes.

Table 3: Crimes per 100,000

	Mean	Sd
Violent Crime	483.93	318.94
Property Crime	4618.34	1210.46
Murder	7.77	6.88
Rape	33.98	15.07
Aggravated 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

Empirical Model and Estimation

Bacon Decomposition

Two-way Fixed Effects (TWFE) is the standard Difference-in-Differences estimation method. However, its efficacy is limited to situations when treatment occurs simultaneously. Since our data set contains multiple time periods and variations in treatment timing - the laws were implemented in different years across states. Here we would try using Bacon decomposition to solve the problem of using late-treated units compared to early-treated units. By using the binary treatment variable, we will re-estimate the effect of the right-to-carry law on different types of crime by coding a state as “treated” if at any time of that year the law had been implemented. For simplicity of modeling and interpretation, treatment will be the only variable on the right-hand side, we would not control for other covariates.

To focus on the degree of pollution of the TWFE, we only report the weight and estimate of early to late 2x2s and late to early 2x2s. We can see from the chart (Table 5)that late to early 2x2s take account of 0.24 of the TWFE estimate, the influence of later to early treated in the mix is rather large. This is an important finding since the late to early 2x2s are estimated based on counter-factual data. Except for property and robbery crime, the average estimate for the late to early 2x2s has a lower estimate than the early to late 2x2s, this means that the TWFE is being pulled down by the late to early group, this is a crucial drawback in Lott and Mustard’s original modeling, as it could incorrectly prove the effectiveness of the law.

The table below is showing the weight and estimates of each type of crime:

Table 4: Bacon Decomposition Summary

Treated_Variable_(Log)	Type	Average_Estimate	Weight
Rate of Violent Crime	Earlier vs Later Treated	0.076	0.067
	Later vs Earlier Treated	-0.076	0.024
Aggravated Assault Rate	Earlier vs Later Treated	-0.011	0.067
	Later vs Earlier Treated	0.006	0.024
Auto Crime Rate	Earlier vs Later Treated	0.08	0.067
	Later vs Earlier Treated	0.002	0.024
Rape Rate	Earlier vs Later Treated	-0.039	0.067
	Later vs Earlier Treated	-0.082	0.024
Larceny Rate	Earlier vs Later Treated	0.116	0.067
	Later vs Earlier Treated	-0.147	0.024
Murder Rate	Earlier vs Later Treated	0.108	0.067
	Later vs Earlier Treated	0.09	0.024
Burglary Rate	Earlier vs Later Treated	-0.034	0.067
	Later vs Earlier Treated	-0.056	0.024
Property Crime Rate	Earlier vs Later Treated	-0.006	0.067
	Later vs Earlier Treated	0.021	0.024
Robbery Rate	Earlier vs Later Treated	0.083	0.067
	Later vs Earlier Treated	0.087	0.024

Twoway Fixed Effects vs Callaway-Sant'anna

Now, we would try using the Callaway-Sant'anna (CS) method to avoid the problem of late-to-early comparison by only using the never or not-yet treated as controls group through subsetting dataset. This method would split the observations into cohorts based on the time of the treatment, the model of this approach is shown below:

$$ATT_{(g,t)} = E[(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}(X)}}{E[\frac{\hat{p}(X)C}{1-\hat{p}(X)}]})(Y_t - Y_{g-1})]$$

We can see that in all of the groups except the auto theft crime rate, TWFE overestimated the treatment effect by magnitude, in some of the cases (rape, aggravated assault, and robbery) the sign even flipped. By using the CS estimation, we could see that the treatment did not have that much effect as a deterrence to crime, and in the sign flipped cases, the law might actually increase the crime rate. The largest reduction of overestimation is rape at 7% of reduction, followed by aggravated assault, and robbery at around 5.5%.

The following table compares the TWFE model to CS in capturing the effect of the right-to-carry law treatment on the crime rate:

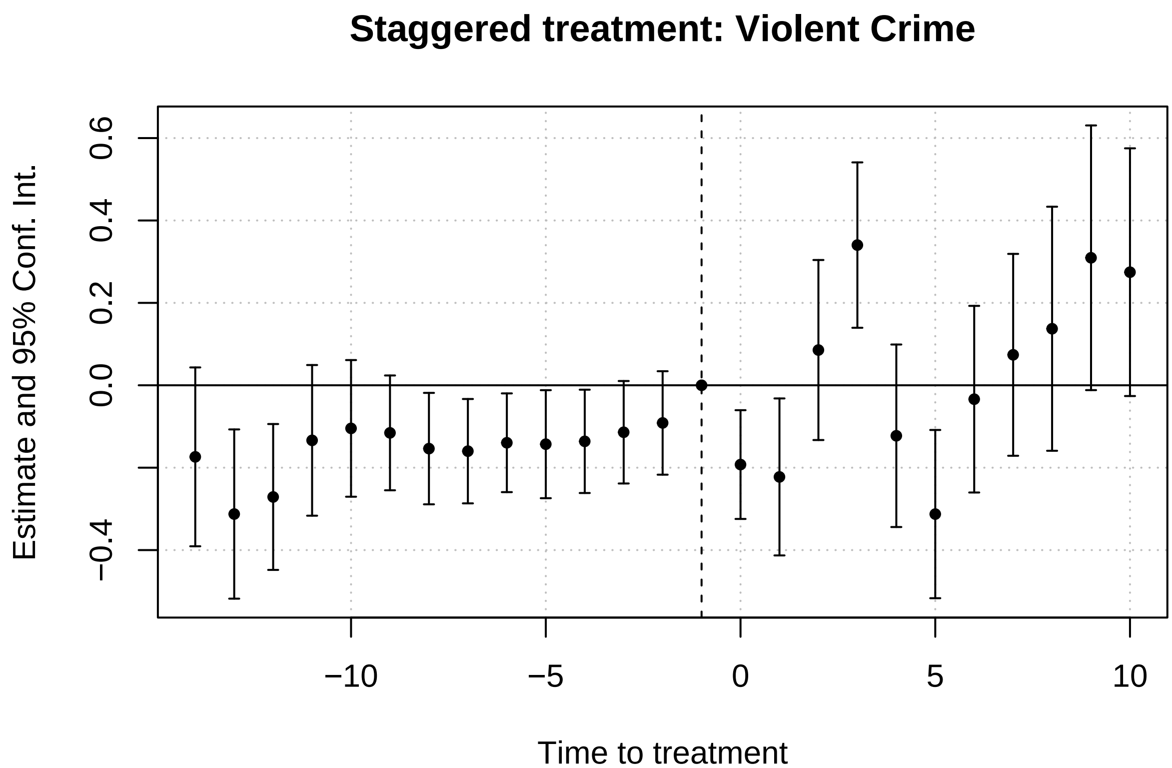
Table 5: TWFE and CS Comparison

outcome	TWFE	CallawaySantAnna	Target Variable
lvio	-0.057	-0.01	Violent Crime Rate
lvio	(0.023)	(0.025)	
lpro	0.009	0.013	Property Crime Rate
lpro	(0.014)	(0.012)	
lmur	-0.05	-0.049	Murder Rate
lmur	(0.04)	(0.026)	
lrap	-0.049	0.02	Rape Rate
lrap	(0.028)	(0.031)	
laga	-0.051	0.005	Aggravated Assault Rate
laga	(0.03)	(0.041)	
lrob	-0.018	0.039	Robbery Rate
lrob	(0.031)	(0.036)	
lbur	-0.024	-0.016	Burglary Rate
lbur	(0.019)	(0.016)	
llar	0.014	0.03	Larceny Rate
llar	(0.013)	(0.016)	
laut	0.034	0.011	Auto Crime Rate
laut	(0.03)	(0.044)	

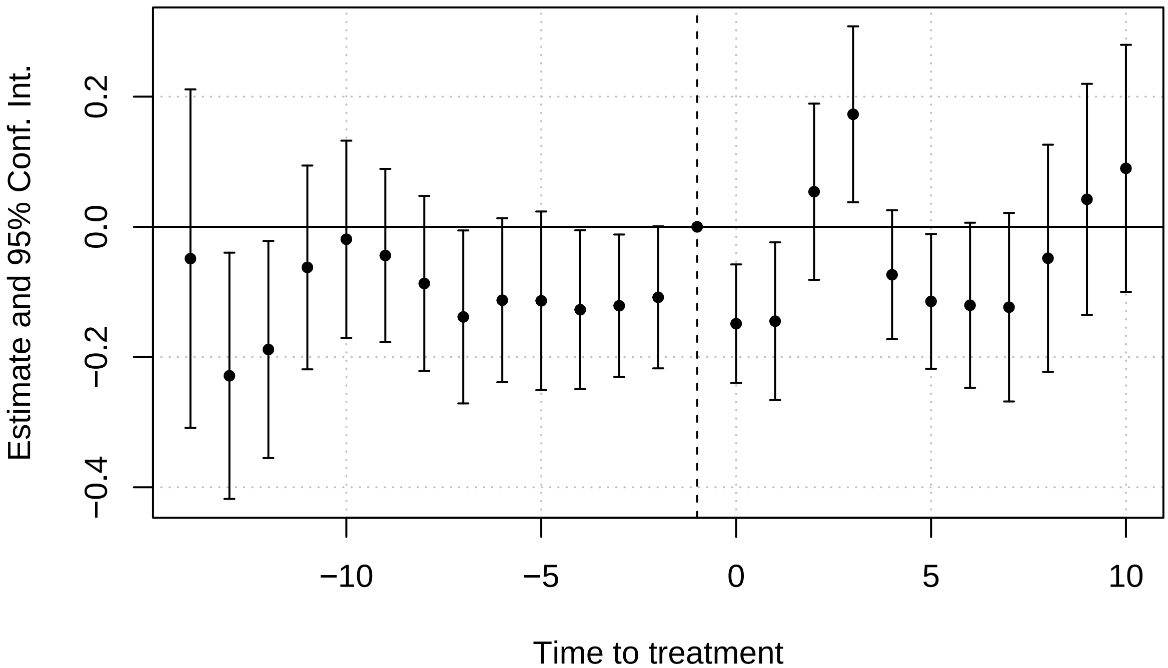
Event Study: Sun and Abraham

Lastly, we will use San & Abraham's approach to solve the differential timing problem. This approach combines the weighted average feature from the Bacon decomposition and the Cohort grouping from Callaway Sant'Anna. This approach allows us to calculate an interaction-weighted estimator, which is more robust in estimating dynamic treatment effects with TWFE under heterogeneity and differential timing, plus we can see the leads and lags by using their model.

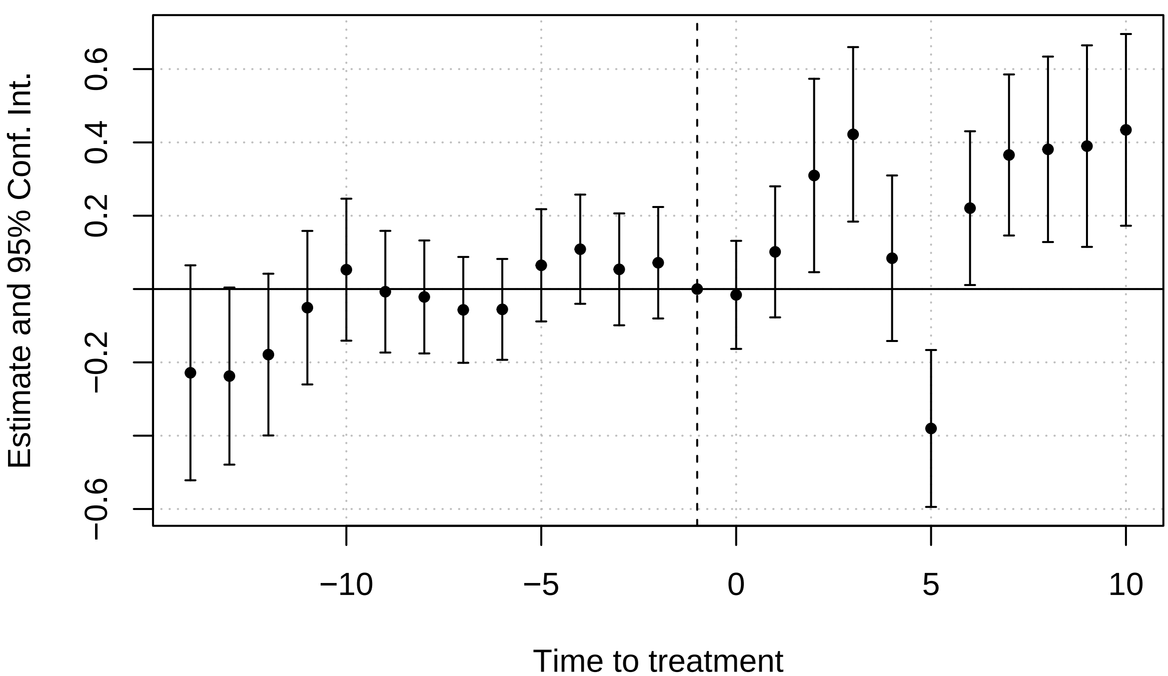
The nine graphs below are showing the Event Study plots for the dynamic treatment effect on each crime, each dots represent the estimated treatment effect at that time and the vertical line is the 95% confidence interval of the estimate. From the graphs, we can see that the parallel trends barely holds, and the estimate for many crime are not significant at a 95% level, we cannot clearly see the effect of the implementation of the law.

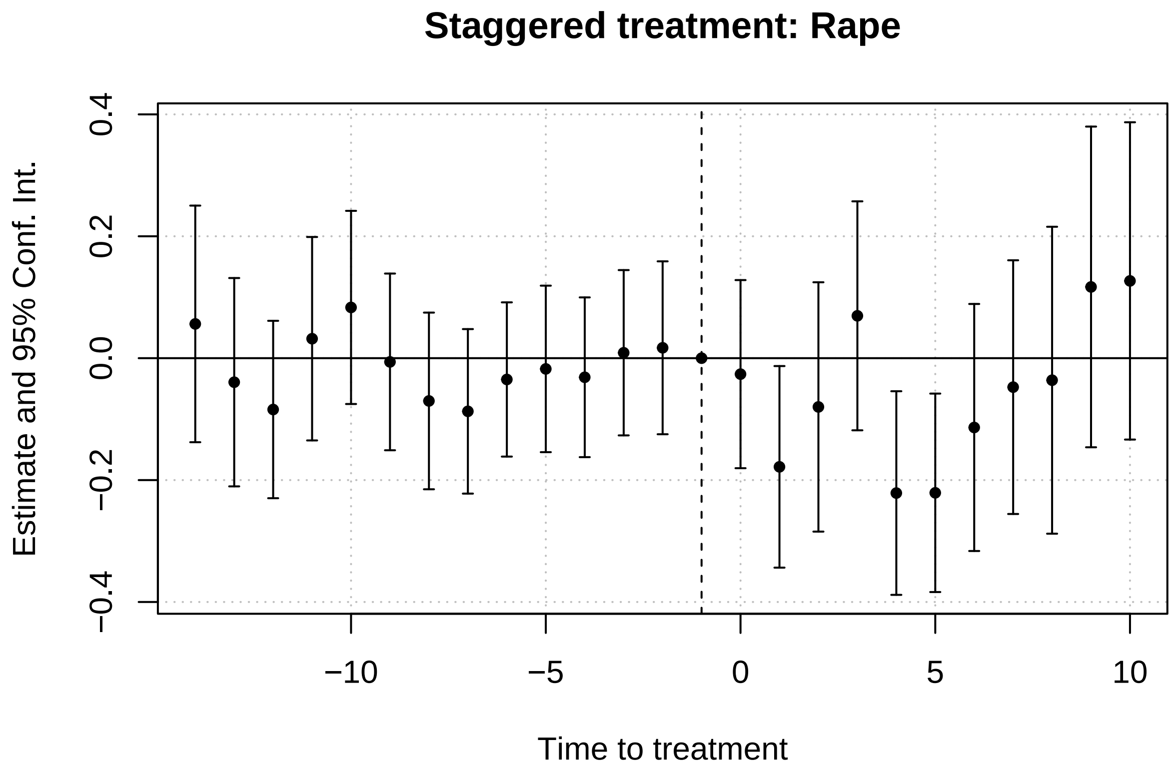


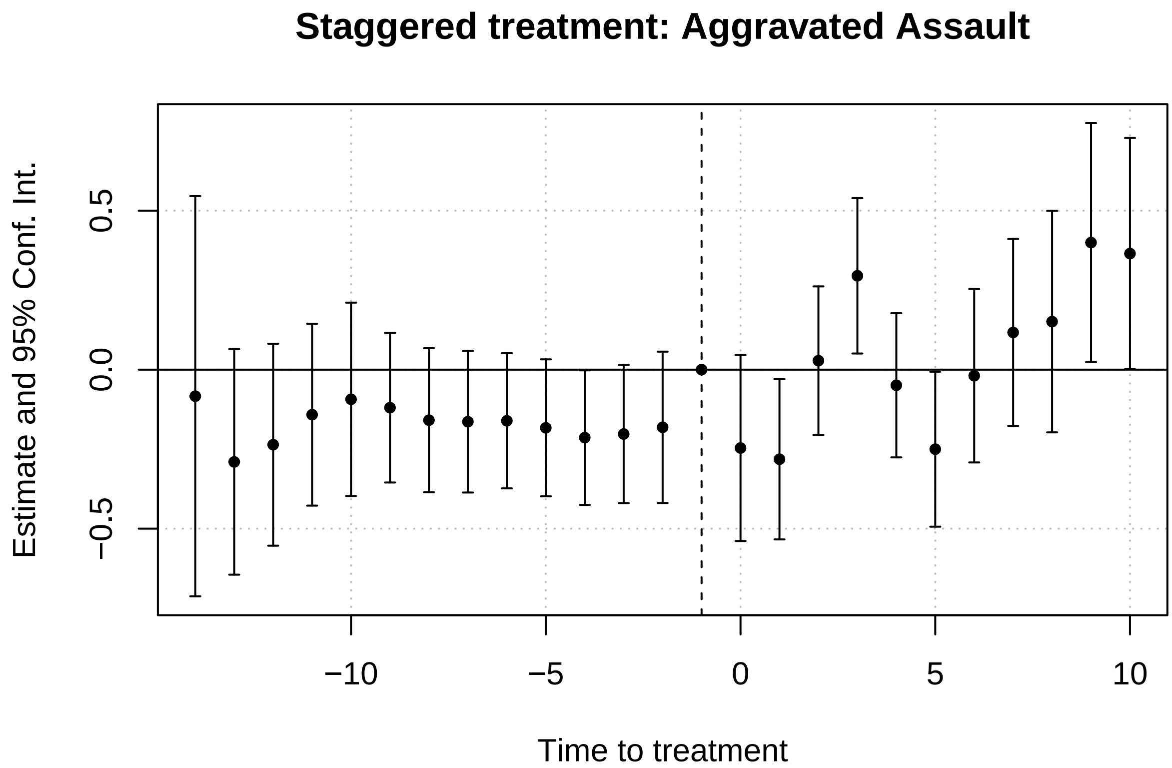
Staggered treatment: Property Crime

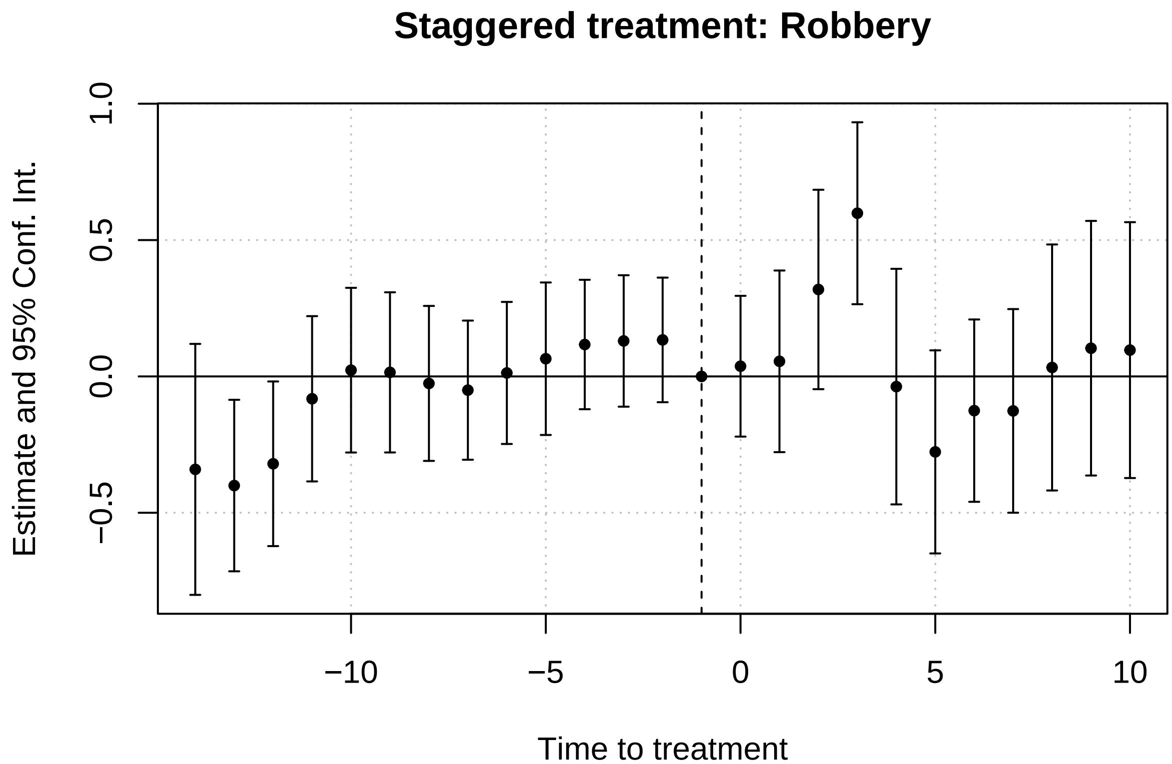


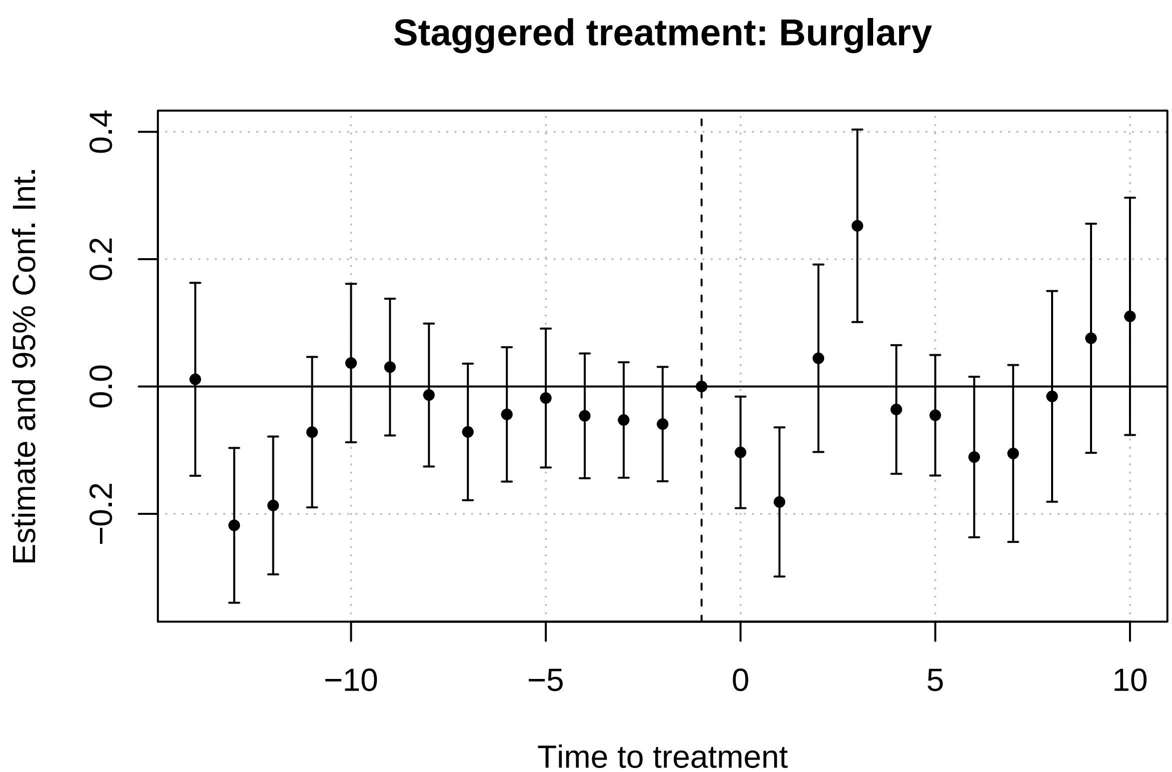
Staggered treatment: Murder

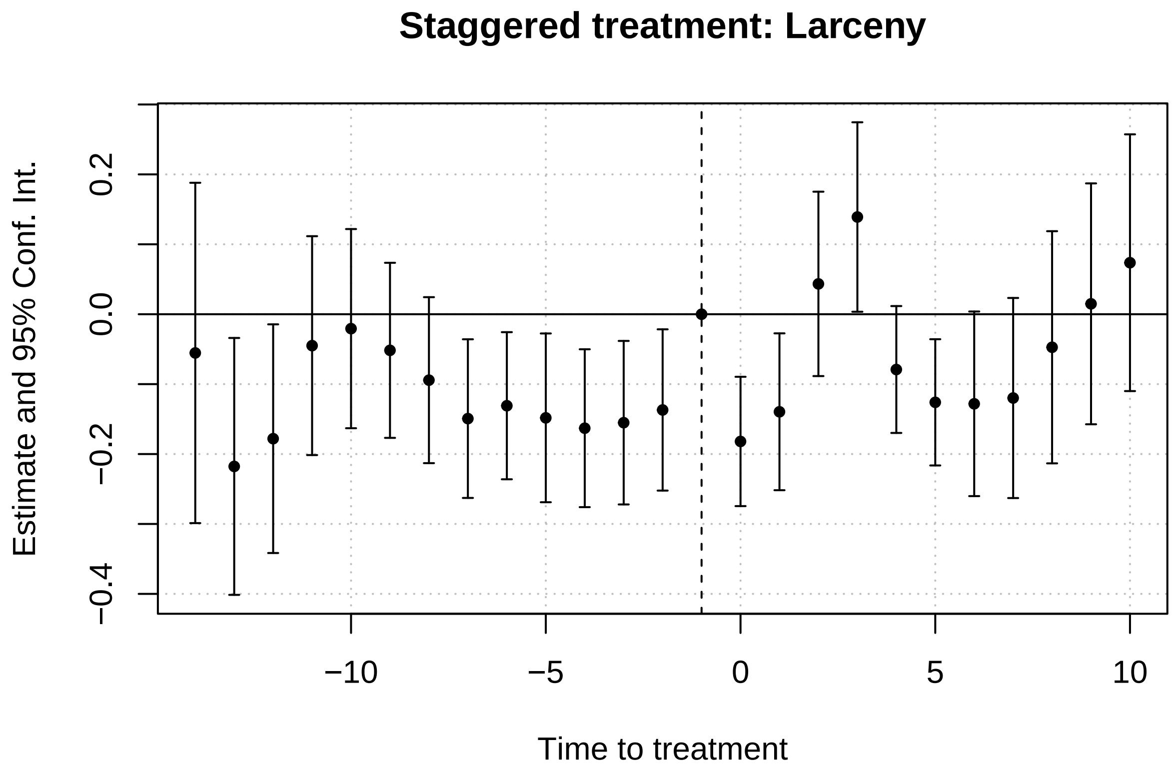


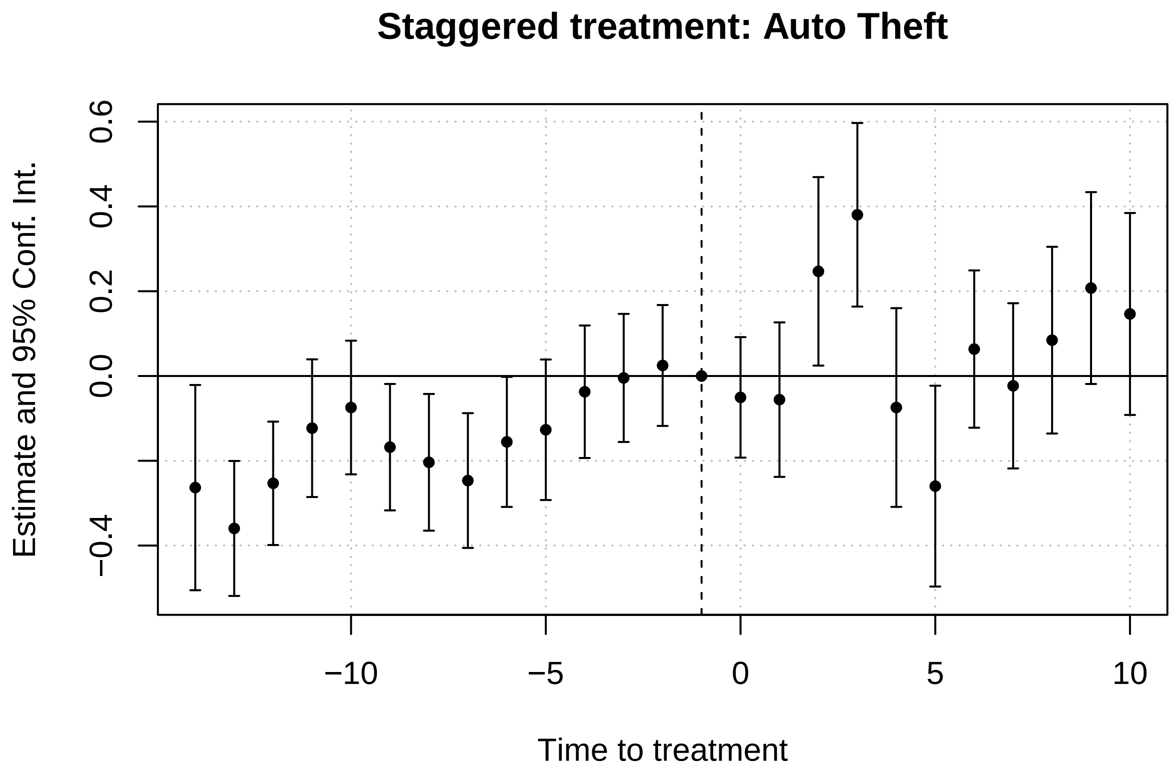

Staggered treatment: Rape
Estimate and 95% Conf. Int.
0.4
0.2
0.0
−0.2
−0.4
−10
−5
0
5
10
Time to treatment


Staggered treatment: Aggravated Assault
Estimate and 95% Conf. Int.
0.5
0.0
−0.5
−10
−5
0
5
10
Time to treatment


Staggered treatment: Robbery
Estimate and 95% Conf. Int.
1.0
0.5
0.0
−0.5
−10
−5
0
5
10
Time to treatment


Staggered treatment: Burglary
Estimate and 95% Conf. Int.
0.4
0.2
0.0
−0.2
−10
−5
0
5
10
Time to treatment


Staggered treatment: Larceny
Estimate and 95% Conf. Int.
−0.4
−0.2
0.0
0.2
−10
−5
0
5
10
Time to treatment


Staggered treatment: Auto Theft
Estimate and 95% Conf. Int.
−0.4
0.0
0.2
0.4
0.6
−10
−5
0
5
10
Time to treatment

Conclusion

After applying the modern approaches of DiD, we estimated some results that diverge from the original paper. In some extreme cases, the effect of the right-to-carry law might even have the opposite effect as the authors originally estimated. Although using state-level data with modern approaches could help us understand the true effect of treatment better, there is still some downside of DiD approach in general, one underlying assumption of these models is that all the treatment groups received the same profile of treatment (or the same treatment at a specific time), this assumption failed to capture the difference among states, and affect the information that our estimate is conveying. Another problem is that DiD estimator provides unbiased treatment only when the parallel trends assumption exists, which is rarely the case in a real-world scenario. Some alternatives to DiD might be looking into: synthetic control, a lagged dependent variable (LDV) regression approach and matching on past outcomes.