Lott and Mustard Replication

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.

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	0.191	0.393
Violent Arrest Rate	802	41.091	22.204
Property Arrest Rate	809	16.918	4.677
Murder Arrest Rate	806	91.299	55.943
Rape Arrest Rate	799	41.023	17.389
Assault Arrest Rate	809	44.625	16.978
Robery Arrest Rate	808	31.458	13.593
Burglary Arrest Rate	809	13.804	4.571
Larceny Arrest Rate	809	18.537	5.196
Autotheft Arrest Rate	808	22.345	37.611
Violent Crime Rate	816	483.926	318.943
Property Crime Rate	816	4618.339	1210.465
Murder Crime Rate	816	7.768	6.882
Rape Crime Rate	816	33.982	15.072
Assault Crime Rate	816	278.755	159.650
Robbery Crime Rate	816	163.421	176.251
Burglary Crime Rate	816	1239.336	417.758
Larceny Crime Rate	816	2968.708	751.023
Autotheft Crime Rate	816	410.295	231.154
Personal Income Rpc	816	9351.821	4689.701
Unemployment Insurance Rpc	816	50.019	38.081
Income Maintenance Rpc	816	115.276	70.953
Retirement Payments Rpc	816	1002.226	546.468
State Population	816	4646787.342	5010349.873
Density	816	355.973	1408.250

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	0.067	0.015
Black Male 1019	816	0.010	0.011
Other Male 1019	816	0.004	0.008
White Female 1019	816	0.064	0.015
Black Female 1019	816	0.010	0.011
Other Female 1019	816	0.004	0.007
White Male 2029	816	0.074	0.012
Black Male 2029	816	0.010	0.010
Other Male 2029	816	0.004	0.007
White Female 2029	816	0.073	0.012
Black Female 2029	816	0.010	0.012
Other Female 2029	816	0.004	0.007
White Male 3039	816	0.066	0.012
Black Male 3039	816	0.007	0.008
Other Male 3039	816	0.003	0.007
White Female 3039	816	0.066	0.012
Black Female 3039	816	0.008	0.010
Other Female 3039	816	0.003	0.007
White Male 4049	816	0.048	0.009
Black Male 4049	816	0.005	0.006
Other Male 4049	816	0.002	0.005
White Female 4049	816	0.048	0.009
Black Female 4049	816	0.005	0.007
Other Female 4049	816	0.002	0.005
White Male 5064	816	0.058	0.010
Black Male 5064	816	0.005	0.007
Other Male 5064	816	0.002	0.006
White Female 5064	816	0.062	0.012
Black Female 5064	816	0.006	0.009
Other Female 5064	816	0.002	0.007
White Male 65o	816	0.043	0.011
Black Male 65o	816	0.004	0.005
Other Male 65o	816	0.001	0.005
White Female 65o	816	0.062	0.017
Black Female 65o	816	0.005	0.008
Other Female 65o	816	0.001	0.005

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 table below.

Table 4: Two Way Fixed Effects Shall Issue Coefficients

Outcome Variable	Coefficient	Std. Error
Violent Crime Rate Log	-0.098	0.021
Property Crime Rate Log	-0.007	0.014
Murder Crime Rate Log	-0.051	0.039
Rape Crime Rate Log	-0.034	0.027
Assault Crime Rate Log	-0.100	0.027
Robbery Crime Rate Log	-0.053	0.031
Burglary Crime Rate Log	-0.046	0.019
Larceny Crime Rate Log	0.003	0.014
Autotheft Crime Rate Log	-0.009	0.028

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.

Please see the appendix for detailed regression tables.

4.2 Bacon Decomposition

To extend the original analysis, we first implement the Bacon Decomposition. The Bacon Decomposition mathematically separates out the coefficients that arise from two way fixed effects estimation. More specifically, the Bacon Decomposition breaks the two way fixed effects regression coefficient into a few important parts: (1) the estimated 2x2 coefficients for each feasible comparison of groups in the sample and (2) the weight assigned to that group for purposes of aggregating into a final two way fixed effects coefficient. The major value in this approach is that we can see and assess the coefficients associated with each comparison of groups (the 2x2s) and the weight they are assigned for production of the final two way fixed effects coefficient. Importantly, this context is fitting because we have many combinations of treatment groups in our data due to the many states being treated at different points in time.

We note that one important difference, and the reason that the coefficients in each of the following tables for the "Total TWFE" line do not correspond to those presented in the prior section, is we do not apply control variables in the bacon decompositions.

For each of the tables below, we can see that the weights are identical. This is because the treatment variable (shall issue law) is the same for each regression, regardless of the outcome crime rate of interest. We see approximately 75 percent of the weighting for the two way fixed effect coefficient placed on the treated vs. untreated comparison, thus anchoring and acting as a core driver of the results. The second largest weight, approximately 16 percent, is placed on the later vs. always treated comparison. The smallest group weights are for the earlier vs. later treated and later vs. earlier treated groups with approximately 6.8 percent and 2.3 percent, respectively.

One interesting issue that the Bacon Decomposition highlights is the contribution of the later vs. earlier treated to the two way fixed effects final results. The estimates associated with this group are particularly problematic in terms of estimating the true treatment effect because they require an additional assumption that is not required for the other 2x2s. In particular, they require the assumption, or belief, that we not only have parallel trends holding across our relevant periods, but we also have homogeneous treatment effects across time for the earlier treated group. Thankfully, in this case, this contingent only contributes a little over 2 percent to the overall estimate.

Table 5: Bacon Decomposition - Violent Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.100	0.068	0.005
Later vs Always Treated	-0.060	0.159	-0.004
Later vs Earlier Treated	0.021	0.023	-0.002
Treated vs Untreated	-0.142	0.749	-0.084
Total TWFE	NaN	NaN	-0.085

Table 6: Bacon Decomposition - Property Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.004	0.068	-0.001
Later vs Always Treated	0.050	0.159	0.009
Later vs Earlier Treated	0.049	0.023	0.000
Treated vs Untreated	0.024	0.749	0.021
Total TWFE	NaN	NaN	0.029

Please see the appendix for the Bacon Decomposition tables for the other seven crime categories analyzed.

4.3 Callaway and Sant'anna

For our second extension of the original analysis we implement the Callaway and Sant'anna estimator. The Callaway and Sant'anna estimator allows us to view estimates of group-time average treatment effects for each group in each time period. Though these are calculated for all comparisons, in reality these statistics are only identified when the time period of treatment for the group is prior to the time period in effect. For periods where this is not the case, we can use these average treatment effects to evaluate the validity of the parallel trends assumption.

To estimate each of the models (for each of the outcome crime rates of interest), we specify each of the necessary grouping variables in addition to the formula for the covariates. As usual, we use year for time, state for identification, and the year in which the state was first treated for states that had shall issue laws instituted in our time frame of analysis. Furthermore, we use the corresponding arrest rate for each crime rate as a covariate in this analysis. After running the model, we aggregate the individual treatment effect estimates at a group level, where the group is a year in which states instituted shall issue laws. Finally, we aggregate to an overall estimate of average treatment effect for each crime rate statistic and present in the following table. We summarize the average treatment effects to this level because many groups do not have sufficient data to calculate accurate confidence intervals.

Table 7: Callaway and Sant'anna Overall ATTs

Outcome Variable	Overall ATT	Std. Error
Violent Crime Rate Log	-0.010	0.025
Property Crime Rate Log	0.013	0.012
Murder Crime Rate Log	-0.049	0.027
Rape Crime Rate Log	0.020	0.028
Assault Crime Rate Log	0.005	0.041
Robbery Crime Rate Log	0.039	0.033
Burglary Crime Rate Log	-0.016	0.016
Larceny Crime Rate Log	0.030	0.016
Autotheft Crime Rate Log	0.011	0.041

Curiously, though we find similar coefficients and directional signs for some of the crimes analyzed, we also see instances where the signs are opposite or are significantly different in order of magnitude. For instance, property crime, rape, assault, robbery, and auto theft all exhibit sign changes between the two methodologies. For violent crime, we find the same sign direction but a significant change in the order of magnitude (10x). We see a similar issue with larceny.

4.4 Event Study (Sun and Abraham)

The third and final extension of the original analysis employs the Sun and Abraham event study estimator. Sun and Abraham's approach incorporates elements of the Bacon Decomposition and the Callaway and Sant'anna estimator, with the focus being on properly removing bias arising from treatment effect heterogeneity. The other key focus of the Sun and Abraham approach is to handle the contamination of lead and lag coefficients and improve estimation of testing for pretrends.

As with the approach presented in the Callaway and Sant'anna section, we estimate a model for each crime rate log outcome with the arrest rate for the associated outcome as the covariate. We use the Sun and Abraham function on treatment year and year, and include state and year fixed effects parameters in our regression. Finally, we present the results in event study figures to visually evaluate pretrends assumptions and apparent cohort average treatment effects. We present the results for Violent Crime Rate Log and Property Crime Rate Log below.

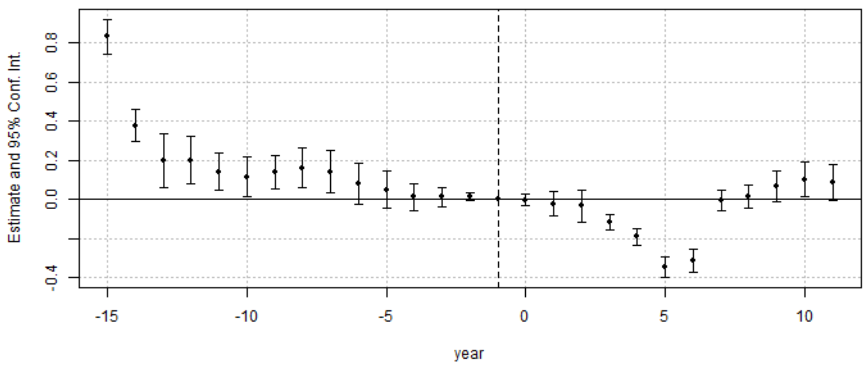

Figure 1: Sun and Abraham Event Study - Violent Crime Rate Log

As shown by the figure, it is not clear the pretrend assumptions hold. Indeed, for many years prior to the treatment year, the estimated effect is statistically significantly different from zero with a 95 percent confidence interval. Additionally, we notice that we see no average treatment effect for the first few years after treatment, before a significant departure for a few years followed by a reversion. The arc is slightly worrisome from a result perspective, since we have significant imbalance for more than three years of treatment in our sample and this is where the most significant results appear. Of the eighteen states with shall issue laws in the sample, ten have more than three years of treatment while eight do not. Thus, the results out past this point are not as strong as those immediately following treatment.

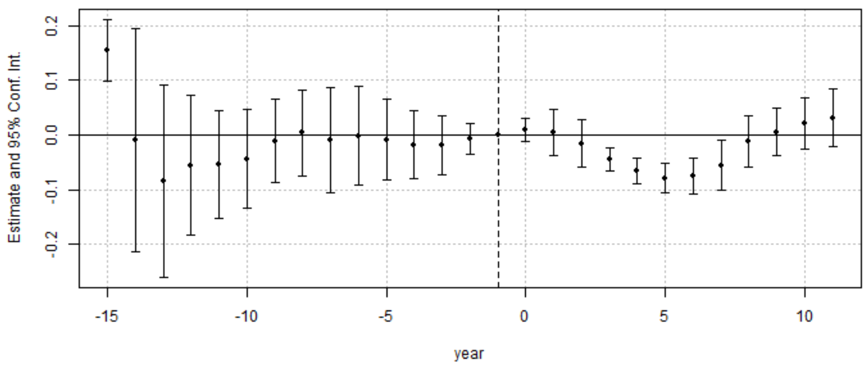

Figure 2: Sun and Abraham Event Study - Property Crime Rate Log

For the Property Crime Rate Log variable, we see that for all but one year prior to treatment it could be that pretrend assumptions hold, though the confidence intervals appear relatively large. Similar to the prior chart, we have an interesting "u" shape after treatment where we see no cohort average treatment effect, some average cohort treatment effect, and no average cohort treatment effect again.

For most of the other crimes analyzed, we see similarly erratic and inconclusive shapes. In many instances the pretrend assumptions appear to hold, but not all. For instance, the Assault Crime Rate Log stands out as the pretrend assumptions do not appear to hold, and we actually see in later treatment years a *positive* average treatment effect.

Please see the appendix for the Event Study figures for the other seven crime categories analyzed.

5 Conclusion

Through this replication and extension, we have shown four different estimators applied to the same data can yield different and interesting results. We first estimated the fixed effects model consistent with the original approach by Lott and Mustard, albeit applied to state level data rather than county level. We then dug in further to the meaning and composition of the resulting fixed effects coefficients by applying the Bacon Decomposition. Finally, we applied the Callaway and Sant'anna alternative estimator and the Sun and Abraham event study to get more specific group-timing treatment effects and assess bias associated with treatment effect heterogeneity. The application of these various approaches showed just how important estimation approach and a critical eye toward potential sources of bias is when performing independent research. Furthermore, we see how far the study of difference in difference models has come in extracting "more true" casual coefficients. Historically, when studying two groups with one treatment, the assumptions and validation was more straightforward. Now, however, newer more nuanced models are required to support more complex scenarios involving multiple treatment groups receiving treatment at multiple times.

6 Appendix

6.1 Detailed Two Way Fixed Effects Tables

Table 8: 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 9: 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 10: 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.

6.2 Additional Bacon Decomposition Tables

Table 11: Bacon Decomposition - Murder Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.055	0.068	0.005
Later vs Always Treated	-0.038	0.159	-0.001
Later vs Earlier Treated	0.019	0.023	0.000
Treated vs Untreated	-0.085	0.749	-0.042
Total TWFE	NaN	NaN	-0.037

Table 12: Bacon Decomposition - Rape Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	-0.026	0.068	-0.003
Later vs Always Treated	-0.200	0.159	-0.031
Later vs Earlier Treated	-0.011	0.023	-0.002
Treated vs Untreated	-0.003	0.749	0.003
Total TWFE	NaN	NaN	-0.032

Table 13: Bacon Decomposition - Assault Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.149	0.068	0.008
Later vs Always Treated	-0.031	0.159	0.001
Later vs Earlier Treated	-0.017	0.023	-0.003
Treated vs Untreated	-0.221	0.749	-0.138
Total TWFE	NaN	NaN	-0.132

Table 14: Bacon Decomposition - Robbery Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.096	0.068	0.007
Later vs Always Treated	0.094	0.159	0.017
Later vs Earlier Treated	0.151	0.023	0.002
Treated vs Untreated	-0.026	0.749	-0.010
Total TWFE	NaN	NaN	0.017

Table 15: Bacon Decomposition - Burglary Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	-0.015	0.068	-0.002
Later vs Always Treated	0.017	0.159	0.005
Later vs Earlier Treated	-0.016	0.023	-0.001
Treated vs Untreated	-0.007	0.749	0.006
Total TWFE	NaN	NaN	0.008

Table 16: Bacon Decomposition - Larceny Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.009	0.068	0.000
Later vs Always Treated	0.048	0.159	0.008
Later vs Earlier Treated	0.062	0.023	0.000
Treated vs Untreated	0.035	0.749	0.028
Total TWFE	NaN	NaN	0.036

Table 17: Bacon Decomposition - Autotheft Crime Rate Log

Type	Average Estimate	Group Weight	Weighted Estimate
Earlier vs Later Treated	0.089	0.068	0.006
Later vs Always Treated	0.189	0.159	0.034
Later vs Earlier Treated	0.099	0.023	0.002
Treated vs Untreated	0.009	0.749	0.026
Total TWFE	NaN	NaN	0.068

6.3 Additional Sun and Abraham Event Study Figures

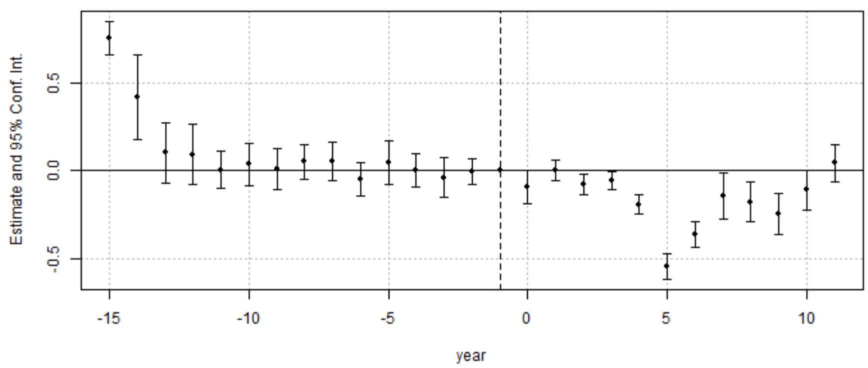

Figure 3: Sun and Abraham Event Study - Murder Crime Rate Log

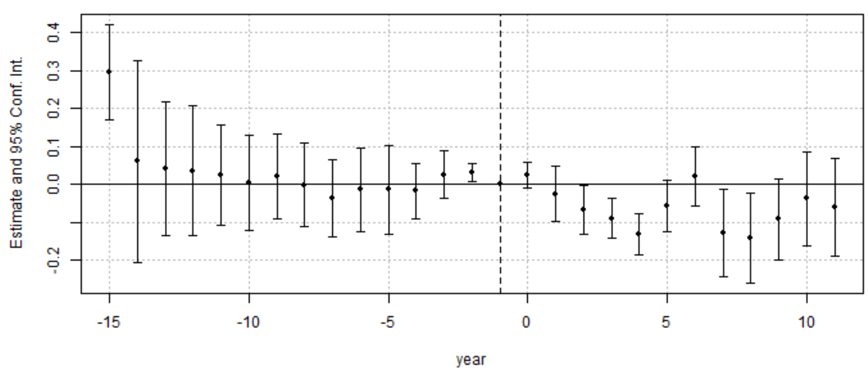

Figure 4: Sun and Abraham Event Study - Rape Crime Rate Log

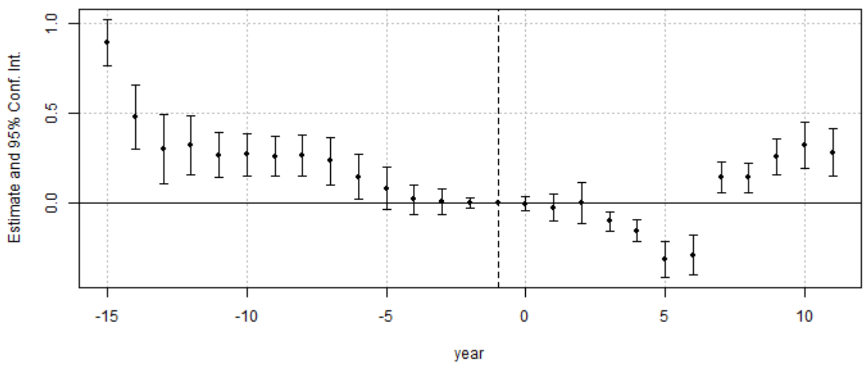

Figure 5: Sun and Abraham Event Study - Assault Crime Rate Log

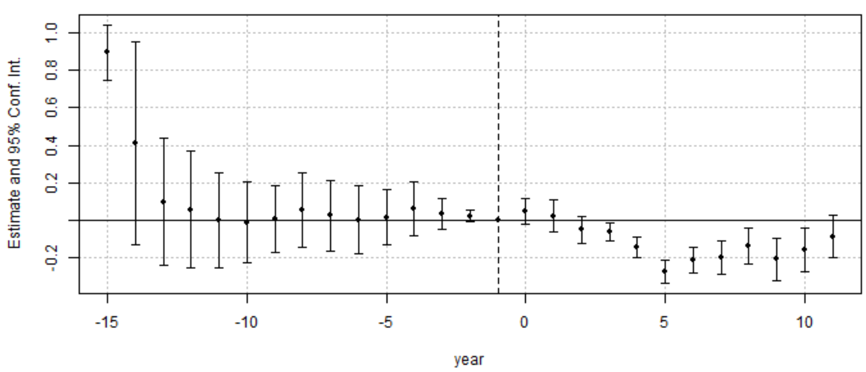

Figure 6: Sun and Abraham Event Study - Robbery Crime Rate Log

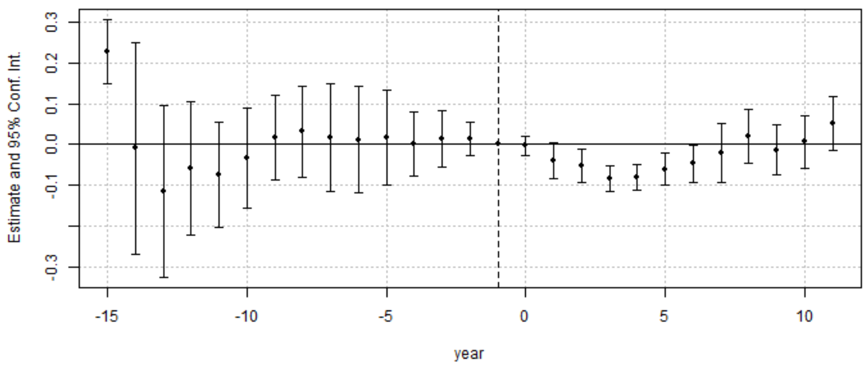

Figure 7: Sun and Abraham Event Study - Burglary Crime Rate Log

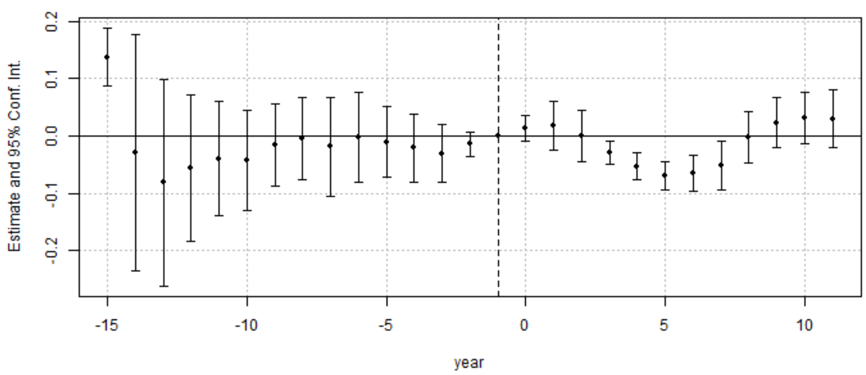

Figure 8: Sun and Abraham Event Study - Larceny Crime Rate Log

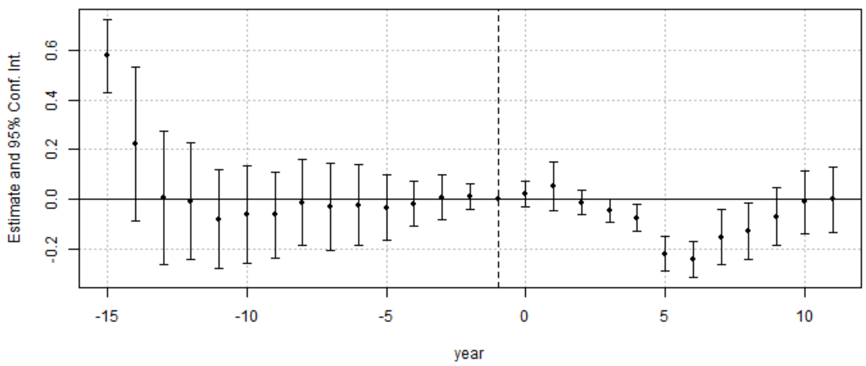

Figure 9: Sun and Abraham Event Study - Auto Theft Crime Rate Log