Lott and Mustard Replication

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Introduction

Deterring crime is a topic the comes across nearly all political debates, with each party having its own solution to the problem. This issue is extremely important to Americans, which is why it is brought up by politicians constantly. People have desire to feel safe and secure in their neighborhoods and homes. One policy initiative that has been proposed and passed by many state legislatures across the United States, is a right to carry law. A passage of this law would give the citizens of that state the ability to carry concealed weapons. The logic being that criminals would be less likely to commit a crime if they reasonably believed an individual may have a gun. In their 1997 paper entitled "Crime, Deterrence, and Right-to-Carry Concealed Handguns, by John Lott and David Mustard, the authors sought to answer the question of how right to carry laws affected crime. In this paper I am seeking to replicate their results using modern difference-in-differences research designs that are robust to the differential timing issue that Lott and Mustard(LM) faced.

Background and Economic Theory

In the original LM study, the authors were looking to find the impact of right to carry laws on crime in the United States. The conclusions from the LM study showed that right to carry laws were main factor causing crime to drop when compared to states that did not adopt a right to carry law. LM coded the laws according Cramer and Kopel's definition of a shall issue state. LM used a classic difference-in-differences two-way fixed effect model with county and year fixed effects. One of the issues with the two-way fixed effects model that LM used is the issue of variable timing of treatments. Over the course of the time period examined states rolled out right to carry laws at various points throughout the time period. I summarize the roll out of right to carry laws by year in Table 1 below.

Table 1: State Roll out of Concealed Carry

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

A right to carry law is simply a law that allows an individual to carry a concealed handgun outside of ones home. Deterrence is the the theory of utilizing laws and policies to shift individuals away from negative behavior. The laws are intended to create a deterrence for criminals to commit crime when they might reasonably believe an individual is armed. When LM performed their analysis they used a two-way fixed effects model to identify the effect of the passage of these right to carry laws. The regression results from LM indicate that 5 of their variables of interest are significant at the 95% level (Violent Crime, Murder, Aggravated Assault, Robbery, and Burglary) and two on the cusp of significance at the 95% level (Rape, and Property Crime). This does not match the results from this replication, although we are supposedly using the same or very similar data. The results from the LM study show that an issuance of a right to carry law resulted in approximately a 5% drop in violent crime and a rise in property crime of about 2.5%. The authors attribute this to a substitution effect where property crimes are less likely to have an encounter between individuals and criminals.

Data

In the original Lott and Mustard paper, the authors used county level crime data for their analysis. For this replication I will be using state level crime data for a variety of reasons. The data set I will be using is a panel data set from 1977 to 1992. The main reason is that the gun laws passed were ultimately passed at the state level, and there are some concerns that county level data will have much more measurement error than at the state level. I provide a summary of the variables in Table 2 below. In the table we can see the arrest rate broken down by the type of crime committed. The arrest rate is defined as the number of arrests per offense. I also show the crimes committed per 100,000 people broken down by crime type. The presence of a right to carry law in a state is identified by a shall issue dummy. The Violent Crime variable represents murder, rape, aggravated assault and robbery. The Property Crime variable represents burglary, larceny, and auto theft.

Table 2: National Sample Summary Statistics

Variable	N	Mean	St. Dev.
Shall Issue Dummy	816	0.19	0.39
Arrest Rate for a particular crime			
Violent Crimes	802	41.09	22.20
Property Crimes	809	16.92	4.68
Murder	806	91.30	55.94
Rape	799	41.02	17.39
Robbery	808	31.46	13.59
Aggravated Assault	809	44.62	16.98
Burglary	809	13.80	4.57
Larceny	809	18.54	5.20
Auto Theft	808	22.35	37.61
Crime Rate for a particular crime per 100,000			
Violent Crimes	816	483.93	318.94
Property Crimes	816	4,618.34	1,210.46
Murder	816	7.77	6.88
Rape	816	33.98	15.07
Robbery	816	163.42	176.25
Aggravated Assault	816	278.76	159.65
Burglary	816	1,239.34	417.76
Larceny	816	2,968.71	751.02
Auto Theft	816	410.30	231.15
Real per capita income data			
Personal Income	816	9,351.82	4,689.70
Unemployment Insurance	816	50.02	38.08
Income Maintenance	816	115.28	70.95
Retirement payments per person over 65	816	1,002.23	546.47
Population	816	4,646,787.00	5,010,350.00
Population per square mile	816	355.97	1,408.25

For each crime there are states for which we have no measurement of arrest rate during various years. This is reflected in Table 2 under the number of observations column.

Empirical Model and Estimation

Two Way Fixed Effects

The two way fixed effects model estimated by LM is shown below in equation 1.

$$Y_{it} = \delta \mathrm{SI}_{it} + \alpha_i + \theta_t + \varepsilon_{it} \tag{1}$$

Y_{it} is represents the logged crime rate for state i at time t. α_i represents state fixed effects, and θ_t represents time fixed effects. SI_{it} is an indicator for the presence of a shall issue law. With the isolation of state and time fixed effects. δ represents the impact of a shall issue law. The results from the regression are shown below in Table 3 below. Only one crime, Violent Crime, is statistically significant at the 90% level. I show that right to carry law results in a 7% drop in violent crime. No other crimes I tested are significantly different from 0. These results are very different than the ones presented in the LM study.

Table 3: Two Way Fixed Effect Regression Results

Dependent Variables:	lvio	lmur	lrap	laga	lrob	lpro	lbur	llar	laut
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Shall issue law dummy	-0.0699*	-0.0550	-0.0378	-0.0641	-0.0299	0.0023	-0.0317	0.0090	0.0193
	(0.0391)	(0.0379)	(0.0453)	(0.0474)	(0.0466)	(0.0215)	(0.0256)	(0.0212)	(0.0401)
Arrest rate for the crime category	-0.0003	-0.0004*	-0.0007	-0.0029***	-0.0015	-0.0023*	-0.0060***	-0.0011	-0.0003**
	(0.0004)	(0.0002)	(0.0006)	(0.0008)	(0.0009)	(0.0012)	(0.0019)	(0.0011)	(0.0001)
Population per square mile	-0.0008***	-0.0008***	0.0003	-0.0007***	-0.0009***	-0.0005***	-0.0006***	-0.0005***	-0.0008**
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Real per capital income data:									
Retirement payments per person over 65	0.0001	0.0002	-7.16×10^{-5}	0.0001	0.0001	-5.94×10^{-5}	6.14×10^{-6}	-6.89×10^{-5}	6.56×10^{-5}
	(0.0001)	(0.0001)	(8.76×10^{-5})	(0.0002)	(0.0002)	(6.72×10^{-5})	(0.0001)	(6.54×10^{-5})	(0.0001)
Personal income	2.16×10^{-5}	4.37×10^{-5}	1.63×10^{-5}	4.75×10^{-5}**	-2.72×10^{-5}	-3.36×10^{-5}*	-3.95×10^{-5}	-3.23×10^{-5}**	-6.45×10^{-5}*
	(1.71×10^{-5})	(2.9×10^{-5})	(2.39×10^{-5})	(2.15×10^{-5})	(3.02×10^{-5})	(1.75×10^{-5})	(2.52×10^{-5})	(1.43×10^{-5})	(3.35×10^{-5})
Income maintenance	-0.0002	-0.0002	-0.0006	0.0007	-0.0009	-0.0002	-0.0002	-0.0002	-0.0006
	(0.0006)	(0.0004)	(0.0007)	(0.0008)	(0.0007)	(0.0003)	(0.0004)	(0.0003)	(0.0007)
Unemployment insurance	-0.0002	-0.0009*	-0.0005	-1.81×10^{-5}	-0.0008	0.0004	0.0007*	0.0004	-0.0006
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0006)
Population	6.05×10^{-8}***	2.43×10^{-8}	-5.76×10^{-8}**	6.64×10^{-8}**	6.12×10^{-8}*	3.08×10^{-8}	3.71×10^{-8}	2.44×10^{-8}	7.66×10^{-8}*
	(2.02×10^{-8})	(2.83×10^{-8})	(2.48×10^{-8})	(2.37×10^{-8})	(3.32×10^{-8})	(1.78×10^{-8})	(2.65×10^{-8})	(1.56×10^{-8})	(3.61×10^{-8})
ppwm1019	-67.75	35.85	-69.55	-17.45	-150.7***	-21.92	-10.01	-31.77	-45.32
	(44.05)	(47.73)	(53.73)	(68.53)	(48.32)	(21.58)	(33.90)	(21.24)	(42.81)
ppbm1019	222.6**	162.7	-49.98	348.1**	197.4	19.08	20.20	-7.450	328.0**
	(77.94)	(98.61)	(103.5)	(120.7)	(130.3)	(61.76)	(96.81)	(58.08)	(119.5)
ppnm1019	357.2	-407.1	-58.62	466.0	228.6	131.4	365.5**	44.66	38.23
	(206.1)	(319.6)	(188.6)	(271.6)	(222.9)	(103.3)	(170.8)	(74.89)	(222.4)
ppwf1019	75.22	-37.48	81.06	19.49	157.1***	28.53	11.36	40.50*	45.59
	(44.76)	(48.25)	(57.46)	(69.48)	(50.97)	(23.08)	(35.18)	(22.67)	(46.77)
ppbf1019	-163.1**	-96.81	44.73	-295.3**	-161.6	2.184	-8.400	25.99	-276.4**
	(75.03)	(98.61)	(98.68)	(112.5)	(111.8)	(56.58)	(86.23)	(54.16)	(111.7)
ppnf1019	-279.5	350.6	153.3	-373.3	-167.8	-146.4	-380.1**	-56.35	-23.43
	(204.6)	(276.4)	(180.9)	(256.0)	(230.8)	(108.8)	(176.9)	(77.93)	(229.5)
ppwm2029	4.834	20.51	3.572	-4.094	44.13*	5.920	10.01	7.838	6.416
	(15.53)	(15.08)	(14.55)	(18.95)	(21.91)	(7.574)	(10.74)	(6.271)	(20.01)
ppbm2029	-4.124	-50.20	134.1	-83.05	-35.76	-27.51	-59.19	-15.55	-122.4*
	(40.84)	(64.15)	(119.7)	(62.56)	(71.33)	(35.65)	(37.43)	(34.36)	(62.94)
ppnm2029	-64.95	120.3	63.76	-64.31	-108.6	-95.23*	-95.75	-75.44	-85.69
	(99.36)	(152.6)	(115.7)	(128.6)	(173.4)	(53.62)	(80.17)	(51.38)	(124.4)
ppwf2029	3.919	-18.12	24.64	14.34	-43.77	-4.257	-8.442	-4.947	-10.94
	(18.29)	(19.03)	(17.35)	(21.46)	(26.90)	(7.981)	(13.61)	(6.581)	(20.68)
ppbf2029	11.31	59.85	-86.21	83.52	27.84	35.33	43.28	31.89	131.1**

	(39.02)	(48.81)	(105.2)	(55.86)	(69.18)	(30.04)	(33.36)	(28.17)	(59.99)
ppnf2029	-25.59	70.11	-133.5	-48.76	5.806	73.69	35.26	68.65	85.28
	(81.63)	(145.0)	(120.4)	(91.94)	(141.2)	(56.41)	(78.28)	(55.08)	(121.6)
ppwm3039	66.12^{**}	-2.524	18.23	90.86^{***}	42.24	9.804	0.1991	6.732	62.16^{*}
	(24.93)	(40.22)	(30.65)	(30.37)	(43.76)	(12.36)	(17.87)	(11.79)	(31.75)
ppbm3039	-4.726	-40.59	-313.9^{***}	66.87	51.70	95.98^{**}	94.93	88.46^{*}	244.6^{**}
	(64.73)	(63.38)	(105.5)	(86.36)	(95.06)	(44.39)	(57.06)	(41.53)	(94.63)
ppnm3039	340.1^{*}	-111.2	162.8	328.4	287.5	-9.984	30.62	4.289	-201.6
	(188.4)	(251.4)	(220.0)	(258.0)	(184.2)	(102.3)	(141.2)	(88.54)	(205.6)
ppwf3039	-56.68^{**}	25.85	14.26	-88.71^{**}	-31.30	-8.994	1.800	-3.755	-74.82^{*}
	(26.18)	(41.20)	(28.68)	(30.49)	(48.00)	(15.79)	(21.45)	(14.79)	(36.66)
ppbf3039	8.470	26.24	247.5^{**}	-55.68	-35.66	-74.45^{*}	-61.12	-75.72^{**}	-168.6^{**}
	(48.71)	(51.63)	(86.18)	(66.23)	(67.69)	(35.13)	(42.56)	(33.85)	(76.41)
ppnf3039	-229.0	59.76	-54.63	-179.4	-245.8	-20.01	-66.34	-37.59	163.1
	(144.1)	(164.9)	(174.9)	(213.6)	(145.6)	(76.12)	(100.6)	(70.34)	(182.3)
ppwm4049	-52.13	-24.58	32.74	-101.1^{**}	-15.07	-18.46	-28.19	-19.72	-13.88
	(35.14)	(28.11)	(34.61)	(45.79)	(49.05)	(20.93)	(32.24)	(18.08)	(43.87)
ppbm4049	113.1	-60.37	289.2^{**}	-96.64	371.6^{**}	100.4^{*}	145.8^{*}	132.5^{**}	-119.5
	(94.59)	(99.30)	(127.0)	(130.0)	(128.8)	(47.59)	(73.49)	(47.33)	(85.19)
ppnm4049	-333.5^{*}	117.1	-493.9^{**}	-391.4	-46.94	135.9	145.1	133.7	-24.07
	(167.1)	(335.2)	(187.9)	(226.5)	(156.8)	(92.87)	(137.5)	(85.93)	(144.3)
ppwf4049	55.43	29.66	-26.23	106.5^{*}	11.14	19.69	24.74	22.92	19.11
	(38.70)	(23.30)	(29.99)	(51.78)	(51.51)	(22.07)	(33.50)	(19.70)	(43.43)
ppbf4049	-48.60	187.6^{*}	-252.7^{*}	93.07	-219.3^{*}	-32.46	-87.88	-55.38	184.1^{*}
	(79.49)	(101.0)	(129.5)	(107.8)	(116.1)	(48.47)	(69.42)	(49.43)	(90.10)
ppnf4049	233.4	-38.27	416.2^{***}	247.8	10.32	-131.4	-160.1	-121.8	53.84
	(144.6)	(285.6)	(141.0)	(192.1)	(146.8)	(85.02)	(120.2)	(79.32)	(131.8)
ppwm5064	-23.36	14.29	-90.00^{**}	-39.02	16.78	-21.58	-44.03	-18.10	75.12
	(27.26)	(34.46)	(34.73)	(35.21)	(48.66)	(17.43)	(25.92)	(15.64)	(46.86)
ppbm5064	-16.99	-247.9^{**}	-7.676	-31.53	-141.6	5.521	89.29	-4.910	-145.6
	(86.41)	(101.6)	(100.8)	(101.9)	(123.6)	(62.54)	(80.08)	(61.30)	(103.9)
ppnm5064	2.215	-85.63	-189.3^{**}	-62.64	99.66	85.33	117.7	57.35	-29.55
	(131.4)	(126.1)	(83.93)	(147.0)	(151.8)	(86.37)	(121.8)	(66.58)	(164.1)
ppwf5064	40.93	-8.493	79.72^{**}	66.42^{*}	-22.94	16.73	35.74	16.62	-79.48^{*}
	(23.76)	(30.84)	(30.48)	(32.77)	(38.82)	(16.11)	(23.83)	(14.52)	(41.28)
ppbf5064	-20.25	51.17	18.30	-18.57	110.7	-41.97	-87.64	-27.27	30.85
	(68.95)	(103.7)	(92.04)	(82.16)	(99.34)	(49.12)	(63.49)	(47.65)	(98.86)
ppnf5064	-116.9	-11.46	79.07	-196.3	-1.813	-37.00	-46.45	-12.80	7.151
	(119.6)	(110.9)	(100.8)	(116.1)	(141.5)	(79.40)	(105.8)	(58.82)	(178.6)
Fixed-effects									
state	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									

Observations	802	806	799	809	808	809	809	809	808
R^2	0.97909	0.94701	0.93976	0.96156	0.98311	0.95910	0.95208	0.96166	0.95518
Within R^2	0.40574	0.29930	0.50171	0.44814	0.48069	0.48718	0.46057	0.48721	0.54198

Clustered (state & year) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Bacon Decomposition

The two way fixed effects model has been a workhorse for empirical economic literature, and for good reason. It is intuitive and is able to isolate out the ATT. However recent literature has shown that there may be some underlying issues with the two way fixed effects model. The issue occurs when there is differential timing of treatment under the two way fixed effects model, in this scenario we are using already treated groups as controls. This is not ideal and can add bias to our estimators. The LM study is an excellent example of differential timing as states were issuing laws at different times as shown in Table 1. It turns out the issue is not plainly differential timing, the issue is that we may have heterogeneous treatment effects. If that is the case then TWFE estimator will be biased. Goodman-Bacon (2021) decompose the weighted 2x2's we see that decomposition in Table 4 below. What we see is that we are putting a not insignificant amount of weight on the Later to Earlier treated group, around 2.3%. The reason this is problematic is that we are using an earlier treated group as a control group for a later treated group. If there is a heterogeneous treatment effect that our TWFE estimator is wrong. It is reasonable to assume that there would be heterogeneous treatment effect in this study, which means we can not rely on the TWFE model to have an unbiased estimator.

Table 4: Bacon Decomposition

	Weight	Average Estimate
Violent Crime		
Earlier vs Later Treated	0.0683810	0.07561
Later vs Always Treated	0.1589397	-0.02812
Later vs Earlier Treated	0.0233921	-0.07645
Treated vs Untreated	0.7492871	-0.11202
Murder		
Earlier vs Later Treated	0.0683810	0.07974
Later vs Always Treated	0.1589397	-0.00789
Later vs Earlier Treated	0.0233921	0.00179
Treated vs Untreated	0.7492871	-0.05551
Rape		
Earlier vs Later Treated	0.0683810	-0.03864
Later vs Always Treated	0.1589397	-0.19207
Later vs Earlier Treated	0.0233921	-0.08243
Treated vs Untreated	0.7492871	0.00406
Aggravated Assault		
Earlier vs Later Treated	0.0683810	0.11645
Later vs Always Treated	0.1589397	0.00612
Later vs Earlier Treated	0.0233921	-0.14717
Treated vs Untreated	0.7492871	-0.18354
Robbery		
Earlier vs Later Treated	0.0683810	0.10775
Later vs Always Treated	0.1589397	0.10999
Later vs Earlier Treated	0.0233921	0.08955
Treated vs Untreated	0.7492871	-0.01341
Property Crime		
Earlier vs Later Treated	0.0683810	-0.01052
Later vs Always Treated	0.1589397	0.05383
Later vs Earlier Treated	0.0233921	0.00644
Treated vs Untreated	0.7492871	0.02810
Burglary		
Earlier vs Later Treated	0.0683810	-0.03397
Later vs Always Treated	0.1589397	0.03046
Later vs Earlier Treated	0.0233921	-0.05563
Treated vs Untreated	0.7492871	0.00858
Larceny		
Earlier vs Later Treated	0.0683810	-0.00608
Later vs Always Treated	0.1589397	0.05034
Later vs Earlier Treated	0.0233921	0.02077
Treated vs Untreated	0.7492871	0.03746
Auto Theft		
Earlier vs Later Treated	0.0683810	0.08313
Later vs Always Treated	0.1589397	0.21147
Later vs Earlier Treated	0.0233921	0.08680
Treated vs Untreated	0.7492871	0.03507

Callaway and Sant'anna

Callaway and Sant'anna (2020) seek to rectify the issues we see with TWFE models with differential timing. The group time ATT is what CS seek to estimate, this estimator is the ATT for different groups, that are treated at different times. We can estimate the group time ATT using equation 2 below.

$$ATT(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}(X)}}{E\left[\frac{\hat{p}(X)C}{1-\hat{p}(X)}\right]}\right)(Y_t - Y_{g-1})\right] \tag{2}$$

I estimate the group ATT and summarize the results in Table 5 below. We see that empirically these treatment effects are much smaller than the estimates I generated from the TWFE model. With the standard errors accounted for none are significantly different from 0. This is huge change from the the TWFE model estimated by LM.

Table 5: Callaway Sant'anna Group ATT

	Violent Crime	Murder	Rape	Aggrevated Assualt	Robbery	Property Crime	Burglary	Larceny	Auto Theft
Overall ATT	-0.015	-0.056	0.010	-0.010	0.024	0.024	0.006	0.030	0.030
Std. Er.	0.022	0.028	0.023	0.032	0.033	0.014	0.014	0.016	0.036

Sun and Abraham Event Study

Conclusion