

Online Supplemental Appendix for State recreational cannabis laws and racial disparities in the criminal legal system*

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We estimate the direct and spillover effects of cannabis legalization on longstanding racial disparities in criminal justice outcomes. We find that legalization reduces cannabis possession and sales arrests for White and Black populations, narrowing but not eliminating disparities. We also find spillover increases in hospitalizations involving cannabis and other illegal drugs. However, spillovers on arrests, incarcerations, and crimes involving serious violent or property offenses are insignificant or even decrease. Other illegal drug sales arrests decrease across populations, while illegal drug incarcerations decrease only among White populations. Spillovers on other low-level offenses are insignificant for White but mixed for Black populations.

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Supplementary Materials

A Effective Dates

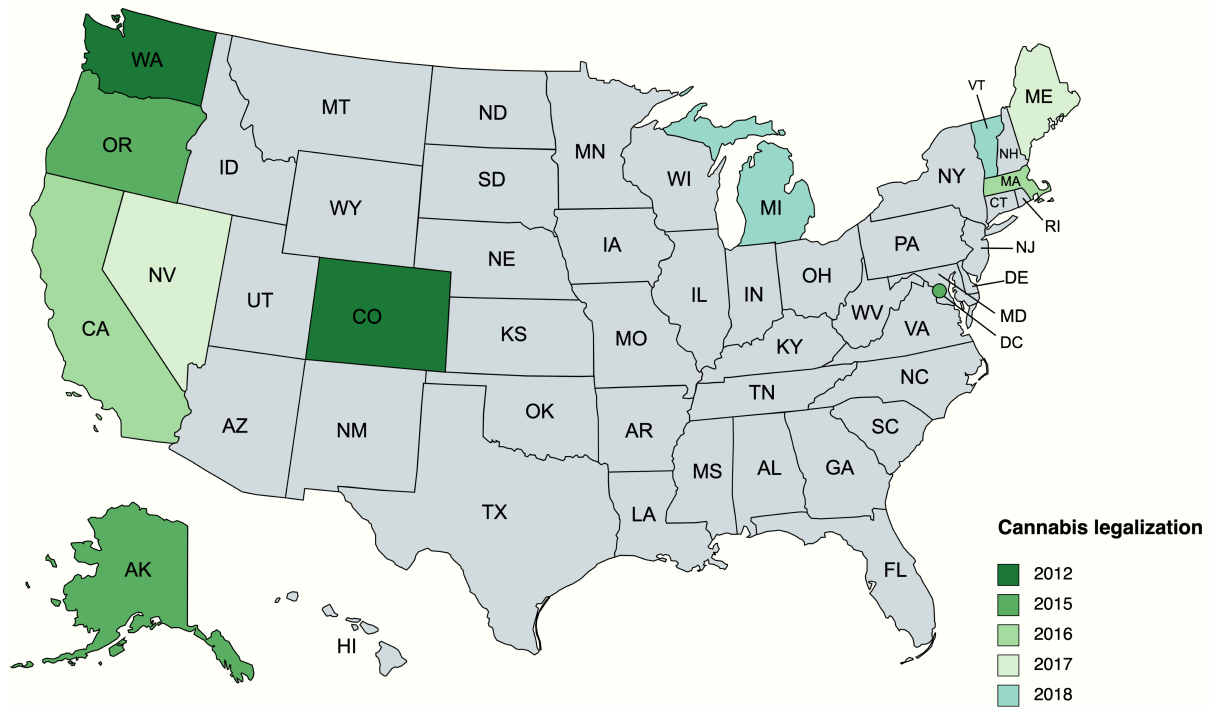


Figure S1: Implementation of recreational cannabis laws by state

Notes: The map shows the spatial roll-out of RCLs across states and over time as of 2019, using data in Table S1. RCL=Recreational cannabis laws.

Table S1: Effective dates of cannabis liberalization policies

State	MCL	CDL	RCL	RCD	CEL
AK	3/4/1999		2/24/2015	10/29/2016	
AZ	11/29/2010				
AR	11/9/2016				
CA	11/6/1996	1/1/2011	11/9/2016	1/1/2018	7/1/2019
CO	12/28/2000		12/10/2012	1/1/2014	6/6/2017
CT	10/1/2012	1/7/2011			
DE	7/1/2011	12/18/2015			8/29/2018
DC	7/27/2010		2/26/2015		
FL	1/3/2017				
HI	6/14/2000				
IL	1/1/2014	7/29/2016			
LA	5/19/2016				
ME	12/23/1999		1/30/2017		
MD	6/1/2014	1/10/2014			10/1/2017
MA	1/1/2013	1/1/2009	12/15/2016	11/20/2018	4/13/2018
MI	12/4/2008		12/6/2018	12/1/2019	
MN	5/30/2014				
MO	12/6/2018				
MT	11/2/2004				
NV	10/1/2001		1/1/2017	7/1/2017	
NH	7/23/2013	9/16/2017			
NJ	6/1/2010				
NM	7/1/2007	1/7/2019			
NY	7/5/2014	7/29/2019			8/28/2019
ND	12/8/2016	5/1/2019			7/10/2019
OH	9/8/2016				
OK	7/26/2018				
OR	12/3/1998		7/1/2015	10/1/2015	
PA	5/17/2016				
RI	1/3/2006	4/1/2013			
UT	12/3/2018				
VT	7/1/2004	1/7/2013	7/1/2018		
WA	12/3/1998		12/6/2012	7/8/2014	7/27/2019
WV	7/1/2019				

Notes: Effective dates of cannabis liberalization policies as of 2019. Information is taken from [ProCon \(2022\)](#); [RAND \(2020\)](#); [Edwards et al. \(2020\)](#); [Grucza et al. \(2018\)](#); [Gunadi and Shi \(2022\)](#); [NORML \(2022\)](#). MCL = Medical cannabis laws, RCL = Recreational cannabis laws, CDL = Cannabis decriminalization laws, RCD = Recreational cannabis dispensaries, CEL=Cannabis record expungement laws.

B Raw Data Plots

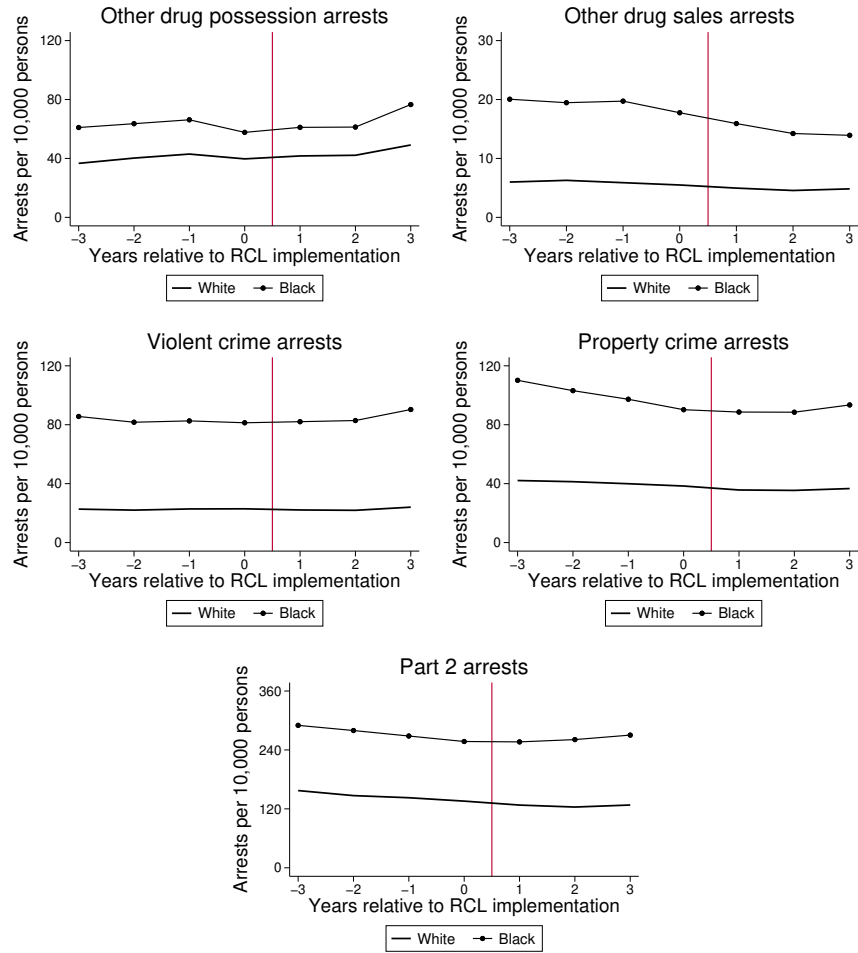


Figure S2: Arrest rates, raw plots

Notes: 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Race-specific population weighted averages calculated for periods relative to RCL implementation. The time $t = 0$ is the period immediately before RCL implementation.

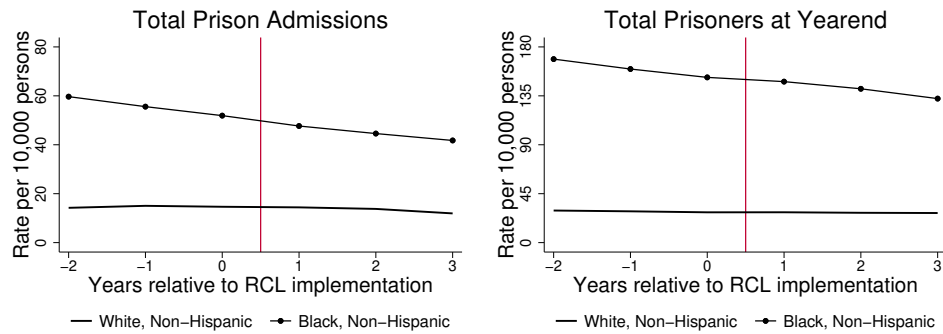


Figure S3: Incarceration rates, raw plots

Notes: Prison admissions are from the 2007-19 National Corrections Reporting Program. Prisoners at yearend are from the 2009-19 National Prisoner Statistics. State-year counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Race-specific population weighted averages calculated for periods relative to RCL implementation. The time $t = 0$ is the period immediately before RCL implementation.

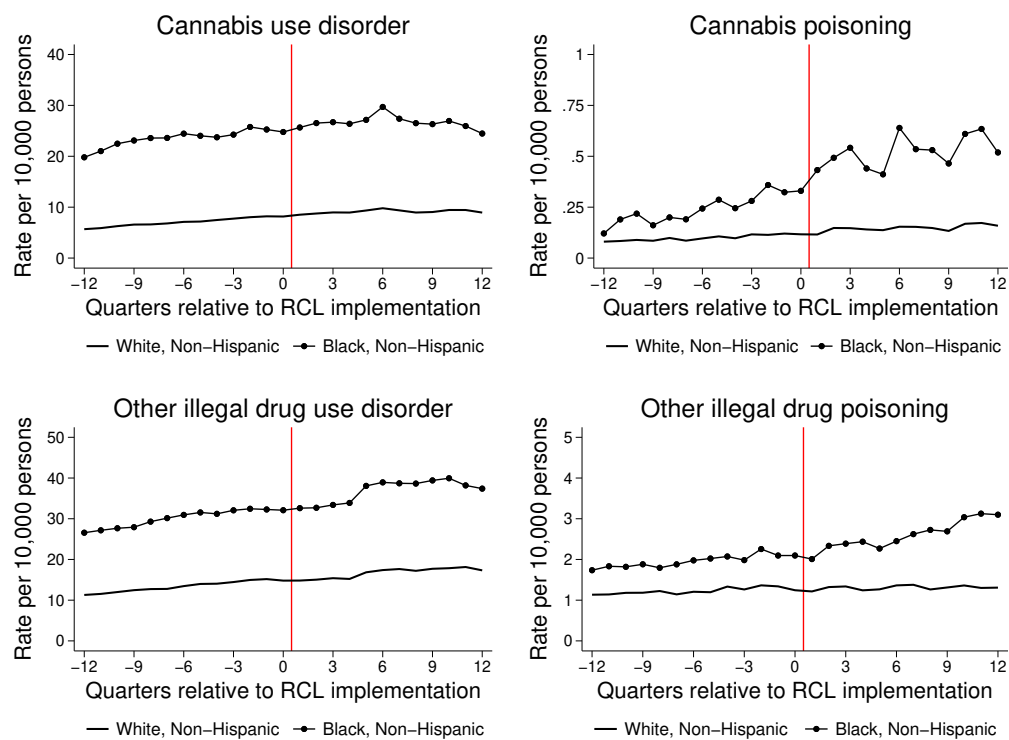


Figure S4: Drug-related hospitalization rates, raw plots

Notes: Hospital discharge data are from the 2007-19 HCUP State Inpatient Databases or from state administrators. The unit of analysis is a state-year-quarter. Counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Race-specific population weighted averages calculated for time periods relative to RCL implementation. The time $t = 0$ is the period immediately before RCL implementation.

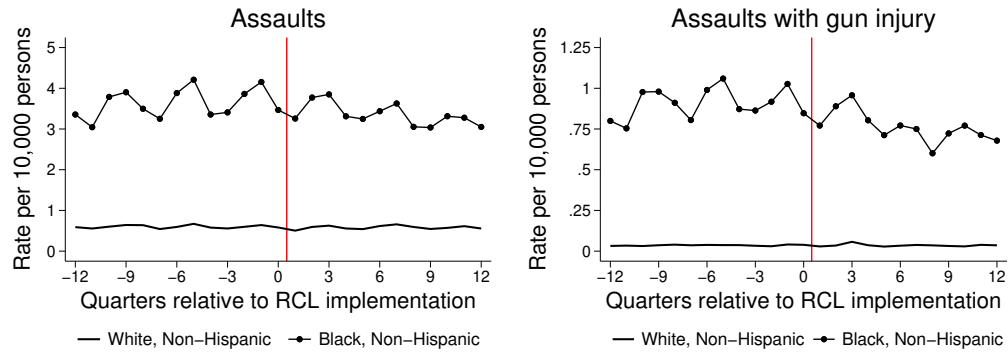


Figure S5: Assault hospitalization rates, raw plots

Notes: Hospital data are from the 2007-19 HCUP State Inpatient Databases or from state administrators. The unit of analysis is a state-year-quarter. Hospital discharge counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Race-specific population weighted averages calculated for time periods relative to RCL implementation. The time $t = 0$ is the period immediately before RCL implementation.

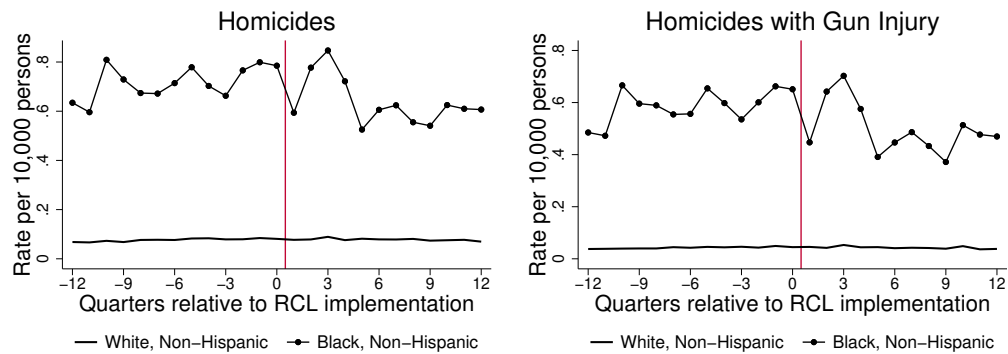


Figure S6: Homicide rates, raw plots

Notes: Death data are from the 2007-19 NVSS Mortality Files. State-year-quarter death counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Race-specific population weighted averages calculated for periods relative to RCL implementation. The time $t = 0$ is the period immediately before RCL implementation.

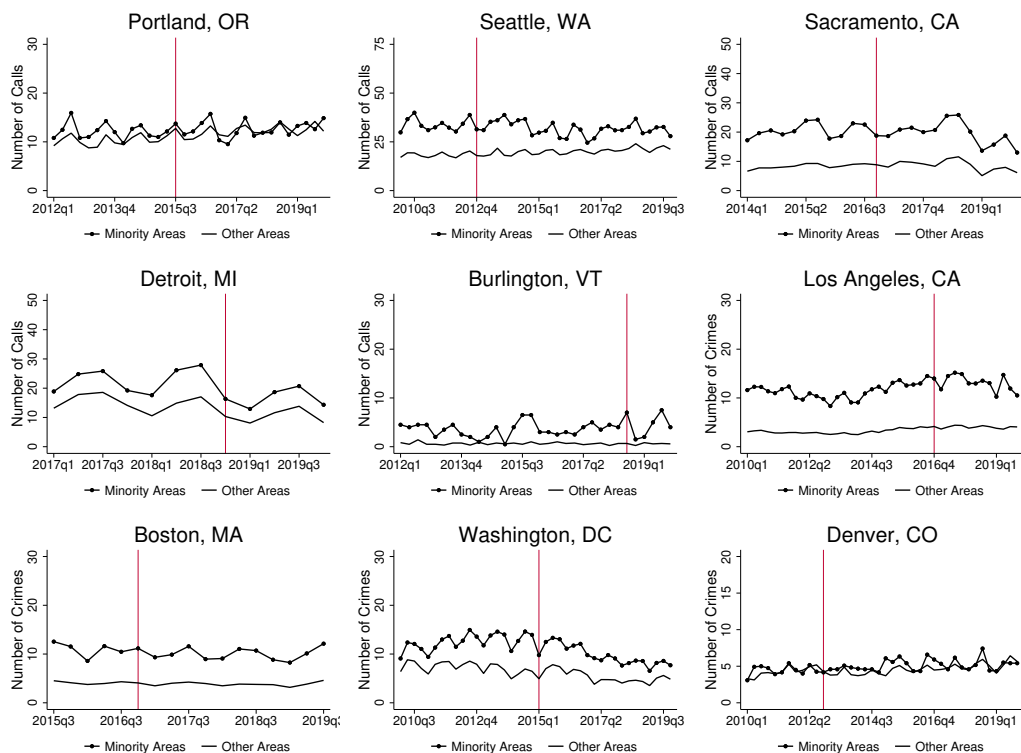


Figure S7: Violent crimes, raw plots

Notes: Calls for service and reported crime data in select RCL cities. Portland (C, E, NE), Seattle (CI, E, NE), Burlington (CI, E, NE), Detroit (CI, E), and Sacramento (CI, PI, E, NE) reflect calls for service. Los Angeles, Denver, District of Columbia, and Boston reflect reported crimes. Outcomes reflect total incident counts for Part 1 violent crimes in a tract-quarter, stratified by minority neighborhoods. Due to differences in collection and reporting of incidents, Part 1 violent crime measurement can be inconsistent across cities. See Sections 2 and F.2 for details. CI=Civilian initiated calls for service. PI=Police initiated calls for service. E=Emergency calls for service. NE=Non-emergency calls for service.

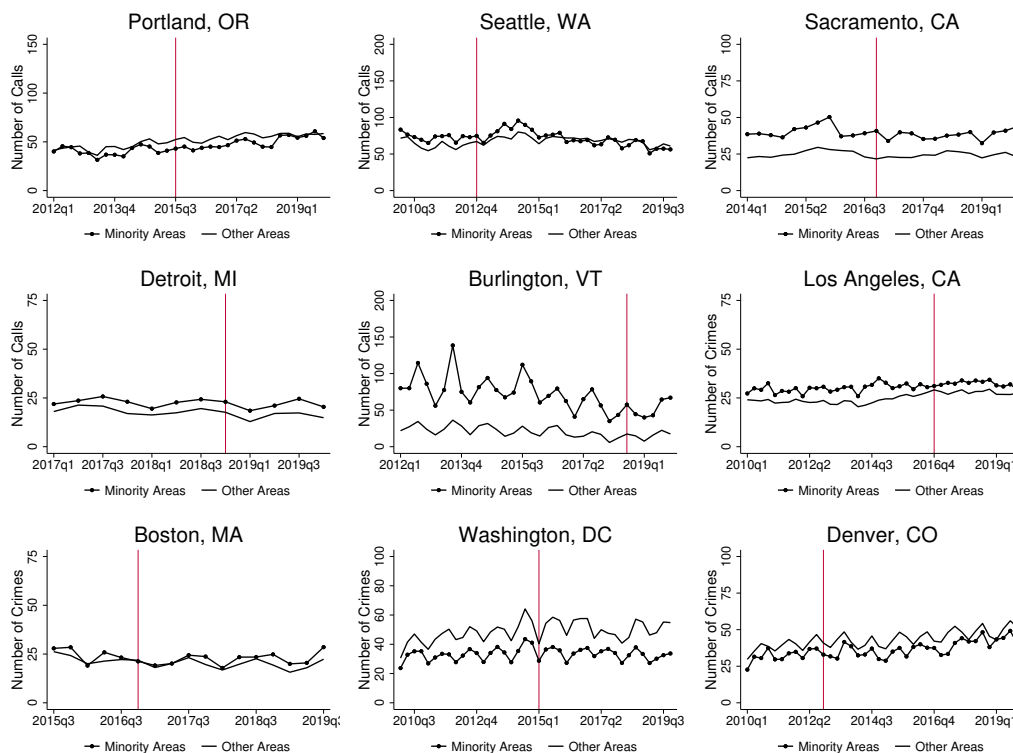


Figure S8: Property crimes, raw plots

Notes: Calls for service and reported crime data in select RCL cities. Portland (C, E, NE), Seattle (CI, E, NE), Burlington (CI, E, NE), Detroit (CI, E), and Sacramento (CI, PI, E, NE) reflect calls for service. Los Angeles, Denver, District of Columbia, and Boston reflect reported crimes. Outcomes reflect total incident counts for Part 1 property crimes in a tract-quarter, stratified by minority neighborhoods. Due to differences in collection and reporting of incidents, Part 1 property crime measurement can be inconsistent across cities. See Sections 2 and F.2 for details. CI=Civilian initiated calls for service. PI=Police initiated calls for service. E=Emergency calls for service. NE=Non-emergency calls for service.

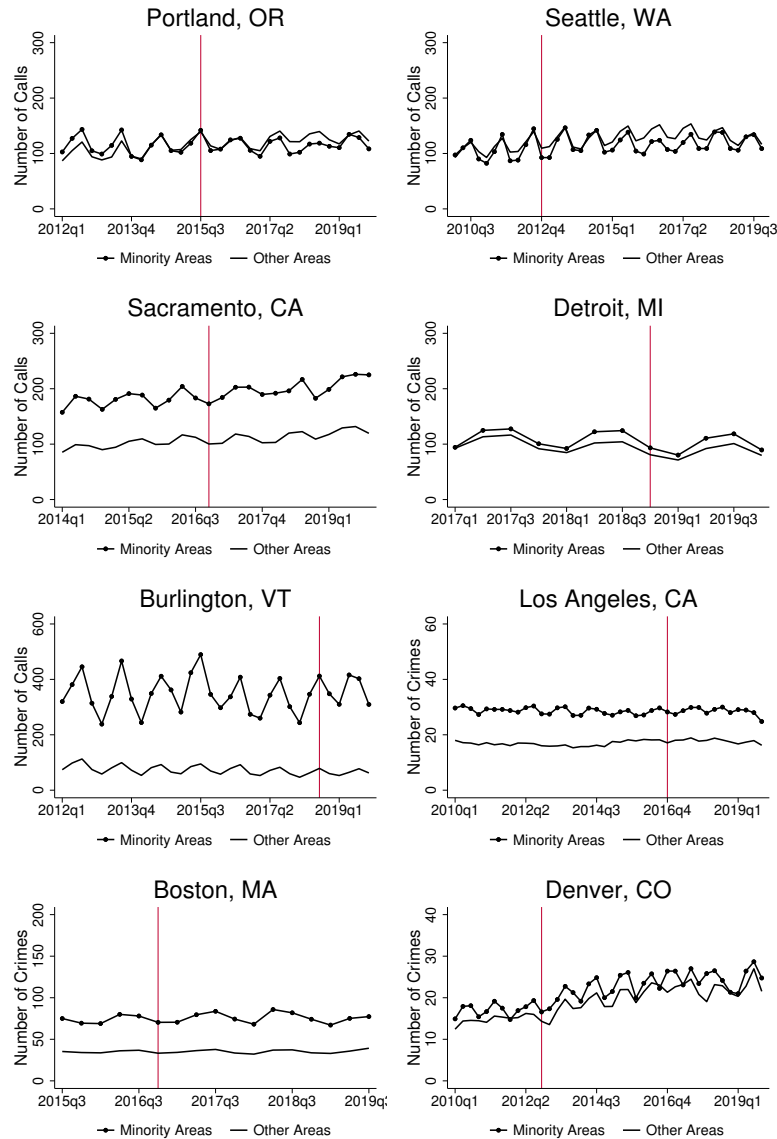


Figure S9: Criminal activity related to Part 2 offenses, raw plots

Notes: Calls for service and reported crime data in select RCL cities. Portland (C, E, NE), Seattle (CI, E, NE), Burlington (CI, E, NE), Detroit (CI, E), and Sacramento (CI, PI, E, NE) reflect calls for service. Los Angeles, Denver, District of Columbia, and Boston reflect reported crimes. Outcomes reflect total incident counts for Part 2 offenses in a tract-quarter, stratified by minority neighborhoods. Due to differences in collection and reporting of incidents, Part 2 measurement can be inconsistent across cities. See Sections 2 and F.2 for details. CI=Civilian initiated calls for service. PI=Police initiated calls for service. E=Emergency calls for service. NE=Non-emergency calls for service.

C Event Study Plots

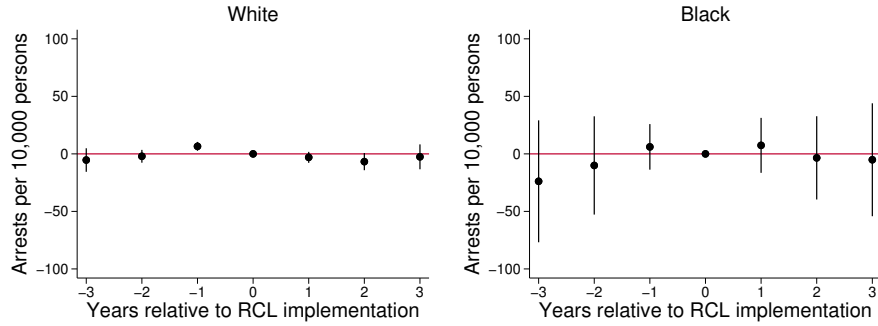


Figure S10: Total arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Coefficients and state-level clustered 95% confidence intervals are based on an event study approach (Equation 2). Regressions are weighted by race-specific population. Controls include the number of reporting agencies and cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

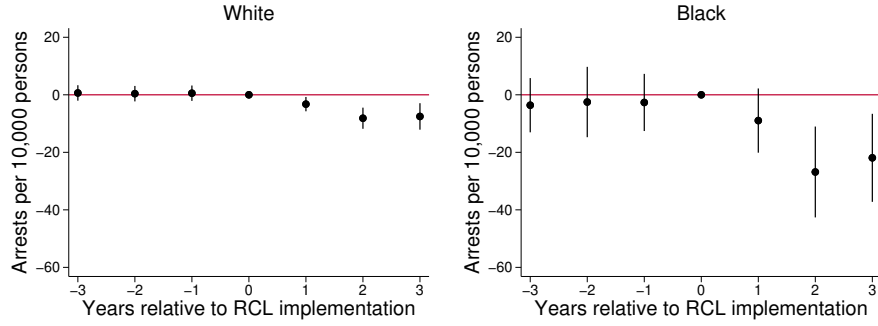


Figure S11: Cannabis possession arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

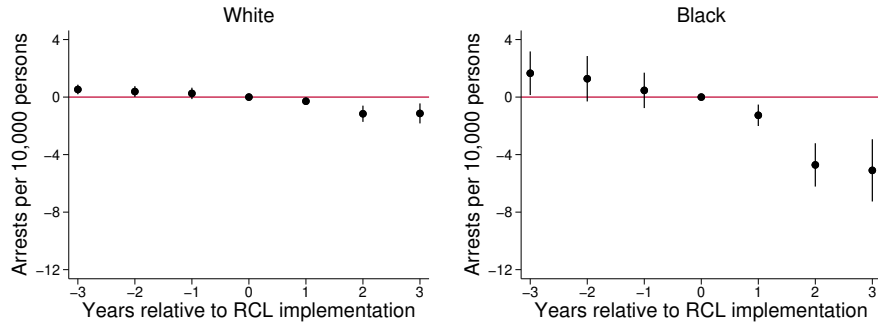


Figure S12: Cannabis sales arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

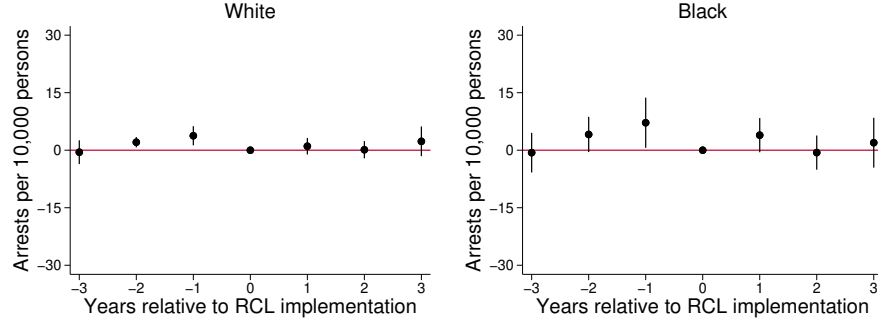


Figure S13: Other drug possession arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

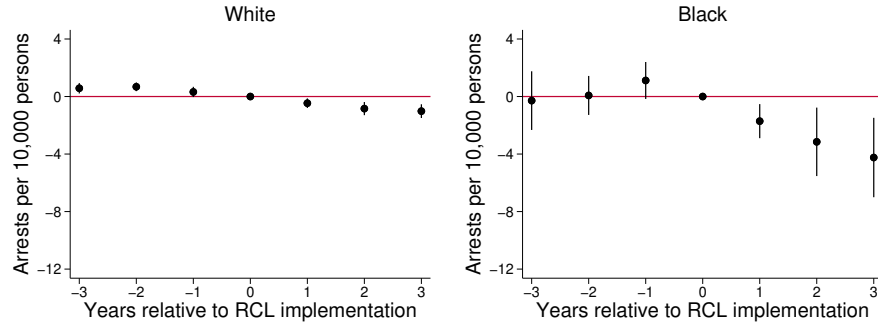


Figure S14: Other drug sales arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

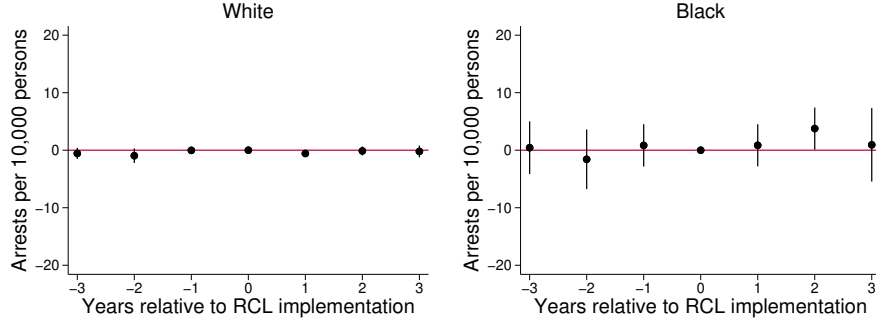


Figure S15: Violent crime arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

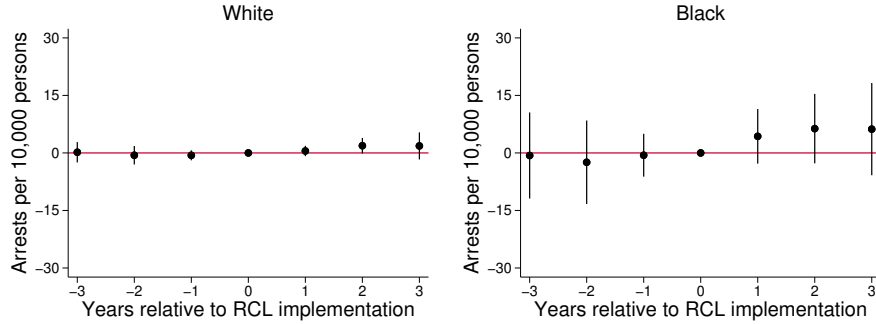


Figure S16: Property crime arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

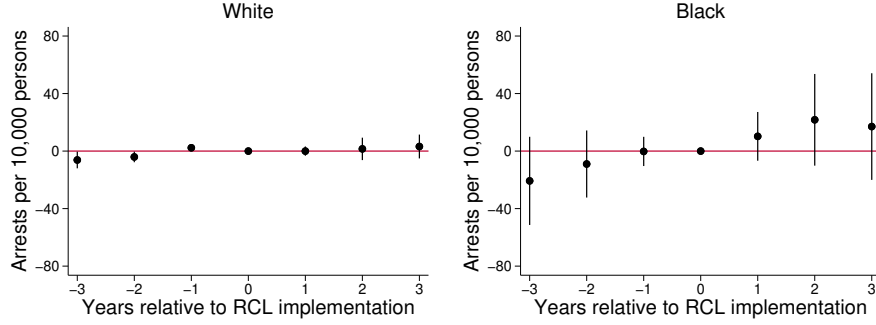


Figure S17: Part 2 arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

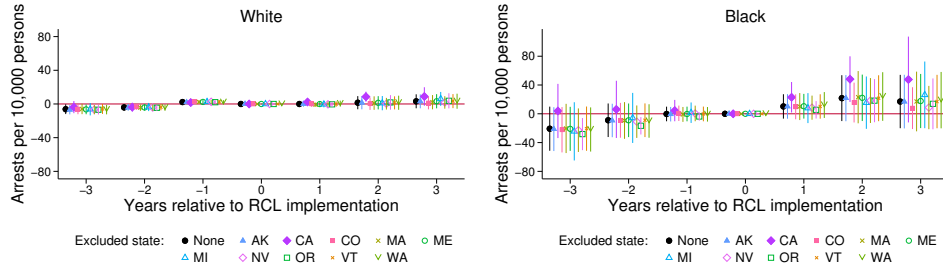


Figure S18: Part 2 arrest rates, excluding one state at a time

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation. Each series of markers corresponds to a separate regression where one RCL state was excluded from the sample.

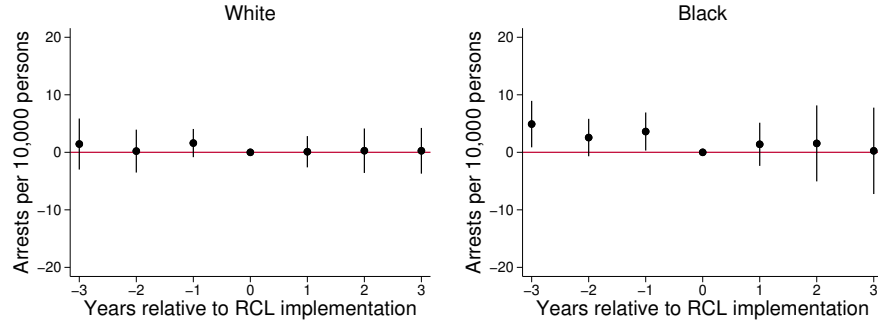


Figure S19: Driving under the influence arrest rates, event study

Notes: Arrests are from the 2007-19 Uniform Crime Reports Arrests by Age, Sex, and Race. County-year counts for a given race are divided by county-year population estimates corresponding to that race, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Event study regressions are weighted by race-specific population estimates. Controls include the number of reporting agencies and cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

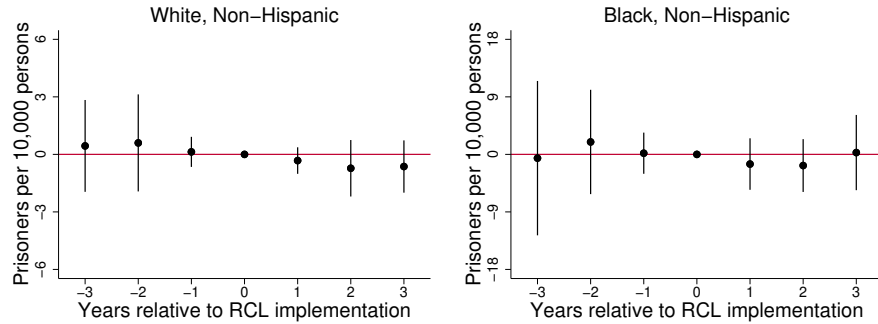


Figure S20: Total prison admissions, event study

Notes: Prison admissions are from the 2007-2019 National Corrections Reporting Program. The unit of analysis is a state-year. Counts for a given race group are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Coefficients and 95% confidence intervals clustered at the state level are based on an event study approach (Equation 2). Regressions are weighted by race-specific population estimates. Controls include cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

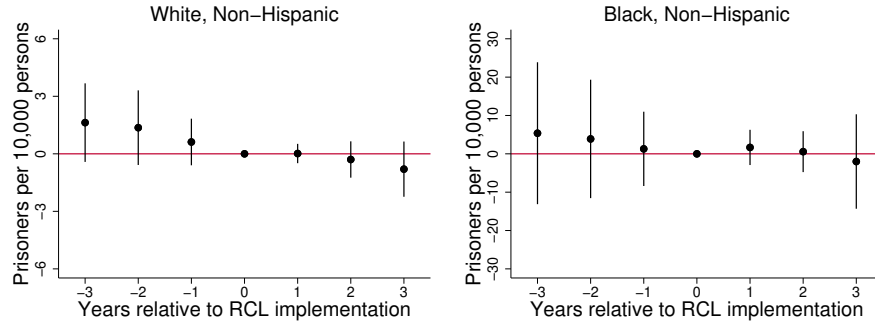


Figure S21: Total prisoners at yearend, event study

Notes: Prisoners at yearend are from the 2009-19 National Prisoner Statistics. The unit of analysis is a state-year. Counts for a given race group are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Coefficients and 95% confidence intervals clustered at the state level are based on an event study approach (Equation 2). Regressions are weighted by race-specific population estimates. Controls include cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

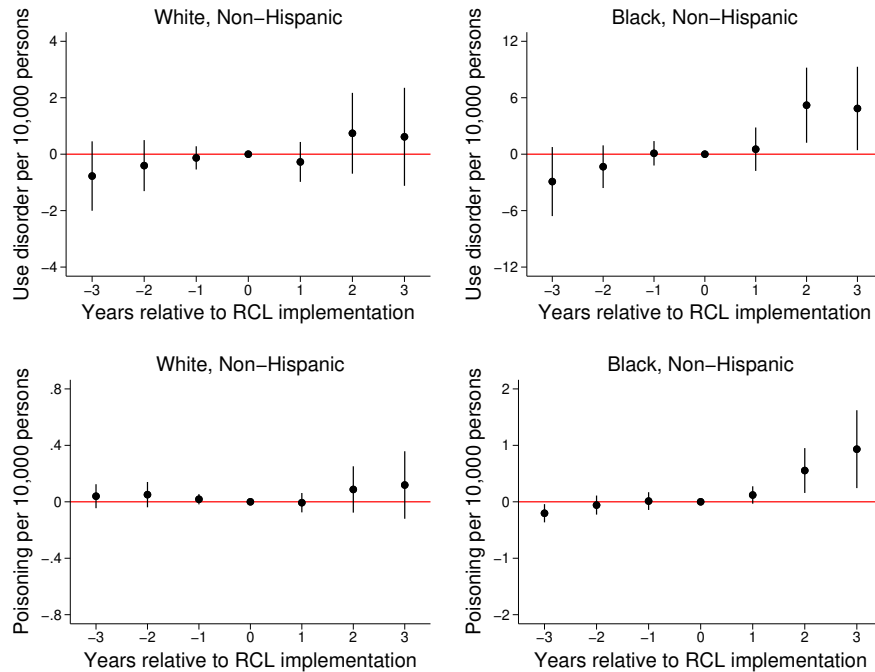


Figure S22: Other illegal drug hospitalizations, event study

Notes: Hospital discharges involving other illegal drug use disorder and poisoning diagnoses (opioids, methamphetamine, cocaine) are from the 2007-2019 HCUP State Inpatient Databases or from state administrators. State-year-quarter counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Event study regressions are weighted by race-specific population. Controls include cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year (four quarters) immediately before RCL implementation.

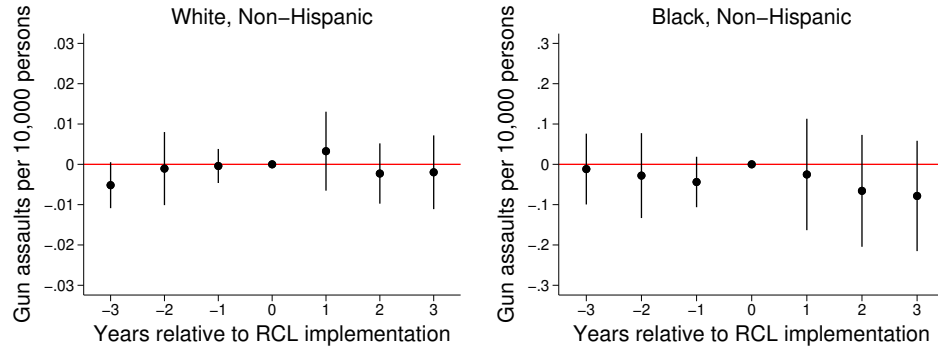


Figure S23: Assault hospitalizations with gun injury, event study

Notes: Hospital data are from the 2007-2019 HCUP State Inpatient Databases or from state administrators. State-year-quarter counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Event study regressions are weighted by race-specific population. Controls include cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year (four quarters) immediately before RCL implementation.

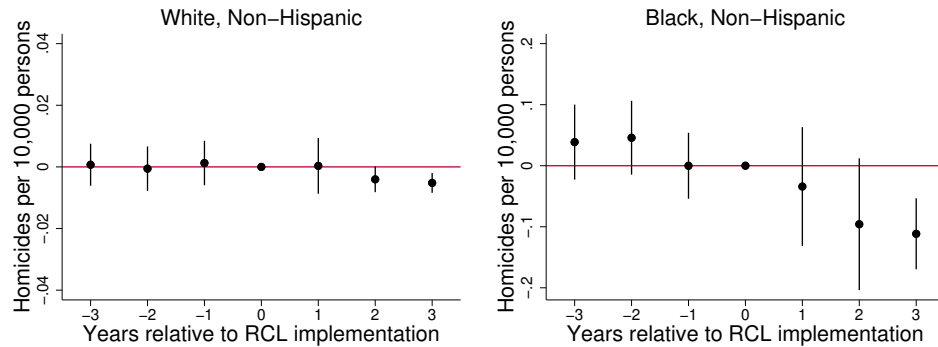


Figure S24: Homicides with gun injury, event study

Notes: Homicide data are from the 2007-2019 NVSS Mortality Files. The unit of analysis is a state-year-quarter. Counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Coefficients and 95% confidence intervals clustered at the state level are based on an event study approach (Equation 2). Regressions are weighted by race-specific population. Controls include cannabis decriminalization laws. The reference year is $t = 0$, the year (four quarters) immediately before RCL implementation. RCL=Recreational cannabis laws.

D Robustness Checks

Table S2: Diagnostic test of percentage and sum of negative weights in TWFE estimators

Rates per 10,000 persons	Percentage	Sum
Cannabis Arrests	1.5%	-0.003
Other drug Arrests	1.5%	-0.003
Non-drug Arrests	1.5%	-0.003
Total Arrests	1.5%	-0.003
Prisoners at Yearend	0%	0
Prisoners Admissions	0%	0
Homicide Deaths	0%	0
CUD Hospitalizations	2.6%	-0.00009
Assault Hospitalizations	2.6%	-0.00009

Notes: This table presents the percentage of all ATT estimates that have a negative weight and the sum of negative weights attached to two-way fixed effects (TWFE) DID estimators of recreational cannabis laws for each analytical sample. Diagnostic tests were performed with the *twowayfeweights* Stata command described in [De Chaisemartin and d'Haultfoeuille \(2020\)](#) and rate outcomes for the Black population.

Table S3: Co-occurrence of drug and non-drug offenses

<u>Panel A: All incidents</u>	
Single offense	88.2%
Part 1 crimes	44.7
Violent crimes	5.9
Property crimes	38.8
Part 2 crimes	43.5
Non-drug crimes	34.9
Drug violations	8.6
Drug possession	7.4
Drug sales	1.2
Multiple offenses	11.8
Involves a drug violation	4.8
Without drug violations	7.0
Total number of incidents	5,642,801
<u>Panel B: Incidents involving drug possession or sales</u>	
Single offense	64.1%
Drug possession	55.5
Drug sales	8.6
Incidents with two offenses	30.8
Only drug violations	22.8
Involves Part 1 crime	2.8
Involves simple assault	0.9
Involves vandalism	0.3
Involves fraud	0.4
Involves gambling	0.0
Involves other Part 2 crime	3.5
Incidents with three or more offenses	5.2
Only drug violations	0.0
Involves Part 1 crimes	2.0
Involves simple assault	0.6
Involves vandalism	0.5
Involves fraud	0.6
Involves gambling	0.0
Involves other Part 2 crimes	3.2
Total number of incidents	757,579

Notes: Incident-level data are from the 2018 National Incident-Based Reporting System (NIBRS). The table shows the share of incidents in 2018 (from reporting agencies) that fall under each categorization. Panel A considers all incidents and Panel B shows incidents involving at least one drug violation. For incidents with three or more offenses, percentages do not add up to the total since the presence of a particular crime is not mutually exclusive with the rest.

Table S4: Effect of recreational cannabis laws on arrests, multiple hypothesis testing

	Drug-defined offenses				Other offenses		Net effects	
	Cannabis		Other Drugs		Part 1		Part 2	Total
	Possession	Sales	Possession	Sales	Violent	Property		
Population	-7.52	-1.34	0.53	-1.04	0.11	2.05	9.66	2.45
Uncorrected p-value	0.009	0.000	0.721	0.002	0.859	0.220	0.049	0.700
Holm p-value	0.012	0.016	1.000	0.014	0.727	0.008	0.010	1.000
Romano-Wolf p-value	0.002	0.002	0.814	0.002	0.814	0.054	0.006	0.814
Mean	12.63	3.41	37.18	7.20	27.06	42.83	159.50	289.81
N	30539	30539	30539	30539	30539	30539	30539	30539
White	-7.31	-1.24	0.55	-1.38	-0.11	0.86	5.86	-2.77
Uncorrected p-value	0.004	0.000	0.778	0.000	0.791	0.599	0.220	0.622
Holm p-value	0.012	0.014	1.000	0.016	0.587	0.335	0.010	0.784
Romano-Wolf p-value	0.002	0.002	0.790	0.002	0.790	0.579	0.048	0.609
Mean	11.76	2.79	38.30	6.28	24.13	41.14	163.09	287.50
N	30539	30539	30539	30539	30539	30539	30539	30539
Black	-18.86	-6.64	-0.66	-4.47	0.50	3.26	32.46	5.58
Uncorrected p-value	0.032	0.000	0.808	0.004	0.891	0.452	0.032	0.801
Holm p-value	0.012	0.016	1.000	0.014	0.774	0.343	0.020	1.000
Romano-Wolf p-value	0.032	0.002	0.974	0.002	0.974	0.607	0.036	0.974
Mean	36.92	13.50	72.47	25.69	88.00	107.19	295.60	639.36
N	30539	30539	30539	30539	30539	30539	30539	30539

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Effect of recreational cannabis laws on arrest rates, rate differences, and rate ratios by race. Counts for a given race are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Rate differences and rate ratios are relative to the White group. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient is based on a separate two-way fixed effects regression (see Equation 1). Regressions are weighted by race-specific population. All regressions include county and year fixed effects. Control variables include the number of reporting agencies and cannabis decriminalization laws. Standard errors are clustered by state. The mean of the outcome variables in RCL states pre-policy is shown. Different p-values that account for multiple-hypothesis testing are shown: baseline (uncorrected) p-values, applying the Holm step-down procedure (Holm, 1979), and controlling for the family-wise error rate (Romano and Wolf, 2005). We use the algorithm developed in Clarke et al. (2020) over 500 replications for our calculations.

Table S5: Effect of recreational cannabis laws on arrests,
controlling for geographic spillovers

Panel A: Cannabis arrests						
Population	-8.859 (2.744)	-8.411 (2.834)	-7.129 (2.781)	-8.123 (2.801)	-7.028 (2.786)	-8.191 (3.016)
White	-8.553 (2.352)	-8.034 (2.434)	-7.087 (2.398)	-7.745 (2.418)	-6.959 (2.404)	-8.325 (2.566)
Black	-25.504 (8.711)	-25.096 (9.385)	-21.120 (9.152)	-23.117 (9.264)	-20.321 (9.218)	-22.939 (9.770)
Panel B: Other drug sales arrests						
Population	-1.037 (0.319)	-1.121 (0.330)	-1.285 (0.356)	-1.075 (0.337)	-1.257 (0.357)	-0.647 (0.307)
White	-1.376 (0.252)	-1.396 (0.278)	-1.529 (0.299)	-1.381 (0.278)	-1.511 (0.300)	-1.322 (0.264)
Black	-4.471 (1.479)	-4.832 (1.638)	-5.418 (1.385)	-4.016 (1.687)	-5.018 (1.434)	-2.678 (0.882)
Panel C: Part 1 arrests						
Population	2.157 (1.940)	2.835 (2.089)	3.976 (2.273)	2.974 (2.080)	4.034 (2.268)	4.256 (2.103)
White	0.746 (1.742)	1.117 (1.873)	1.488 (2.158)	1.374 (1.900)	1.634 (2.167)	1.845 (1.947)
Black	3.759 (6.428)	5.609 (6.745)	10.496 (6.189)	6.029 (6.487)	10.648 (6.162)	6.760 (6.675)
Panel D: Part 2 arrests						
Population	9.669 (4.785)	11.536 (4.654)	14.603 (4.304)	12.953 (4.556)	15.314 (4.322)	11.582 (4.632)
White	5.870 (4.718)	7.675 (4.478)	8.615 (4.253)	8.805 (4.452)	9.337 (4.274)	5.793 (4.226)
Black	32.451 (14.722)	34.774 (14.343)	45.816 (12.447)	39.471 (13.820)	47.796 (12.426)	35.273 (13.631)
Panel E: Total arrests						
Population	2.461 (6.308)	4.848 (6.619)	10.059 (6.391)	6.734 (6.379)	10.907 (6.383)	7.856 (6.776)
White	-2.758 (5.589)	-0.578 (5.781)	1.239 (6.005)	1.052 (5.709)	2.196 (6.028)	-2.065 (6.247)
Black	5.574 (21.997)	9.540 (23.389)	29.594 (18.115)	19.034 (21.568)	33.643 (17.937)	18.245 (20.063)
Controls for spillovers:						
RCL within 0-100 miles	No	Yes	Yes	No	Yes	No
RCL within 100-200 miles	No	No	Yes	No	Yes	No
Inverse distance to nearest RCL	No	No	No	Yes	Yes	No
Sample restrictions:						
Excl. RCL border states	No	No	No	No	No	Yes

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Effect of recreational cannabis laws on arrest rates, by race. Counts for a given race are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient is based on separate two-way fixed effects regression (see Equation 1). Each column adds different control variables that account for potential spillovers of RCLs: conditional on not having an RCL, an indicator for whether there is a county within 100 miles with an RCL in place, whether there is a county within 100-200 miles with an RCL, and the inverse distance to the nearest county with an RCL. The final column excludes all RCL border states from the sample. Regressions are weighted by race-specific population. All regressions include county and year fixed effects. Control variables include the number of reporting agencies and cannabis decriminalization laws. Standard errors clustered by state are in parentheses. Total observations for the main sample is 30524; total observations excluding RCL border states is 23156. States that border any of our RCL states are ID, UT, AZ, WY, NE, KS, OK, NM, WI, IN, OH, NY, CT, NH, and RI.

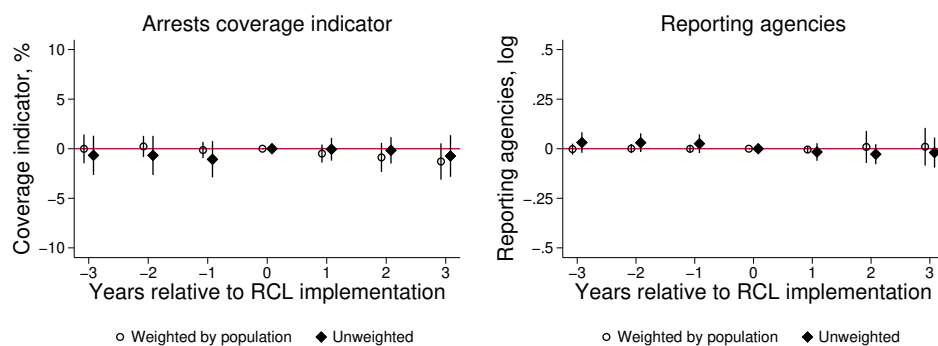


Figure S25: Agency reporting coverage indicator and reporting agencies

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Coverage indicator is a number between 0 and 100% denoting the share of arrests in a county-year that are accounted for in the data. Reporting agencies are the number of police agencies in a county-year that are reporting data to the FBI, in logs. Coefficients and 95% confidence intervals clustered at the state level are based on an event study approach (Equation 2). Hollow markers correspond to regressions weighted by total population; solid markers are unweighted. Controls include the number of reporting agencies and cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

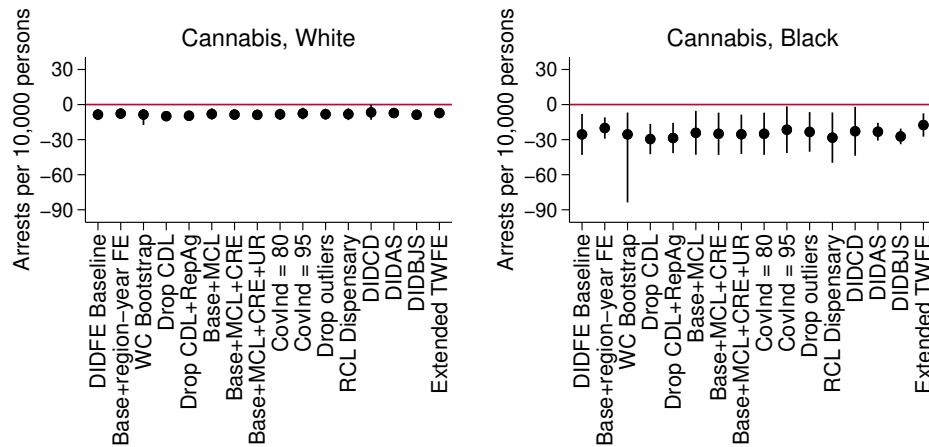


Figure S26: Cannabis arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

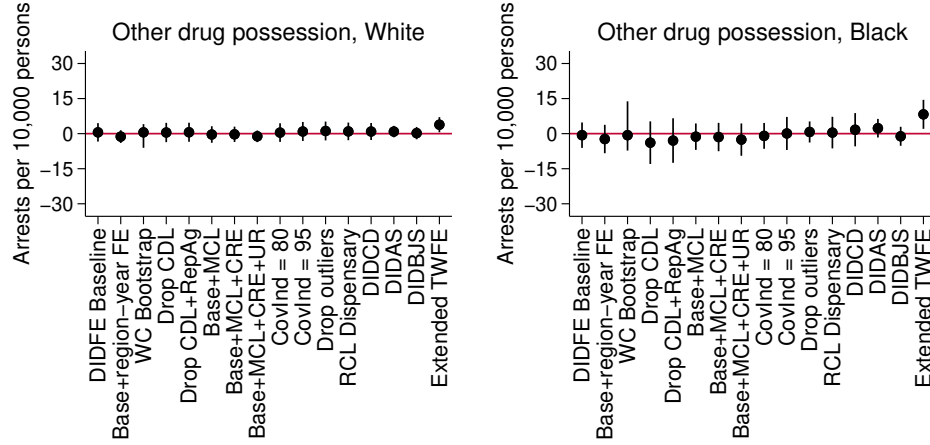


Figure S27: Other drug possession arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

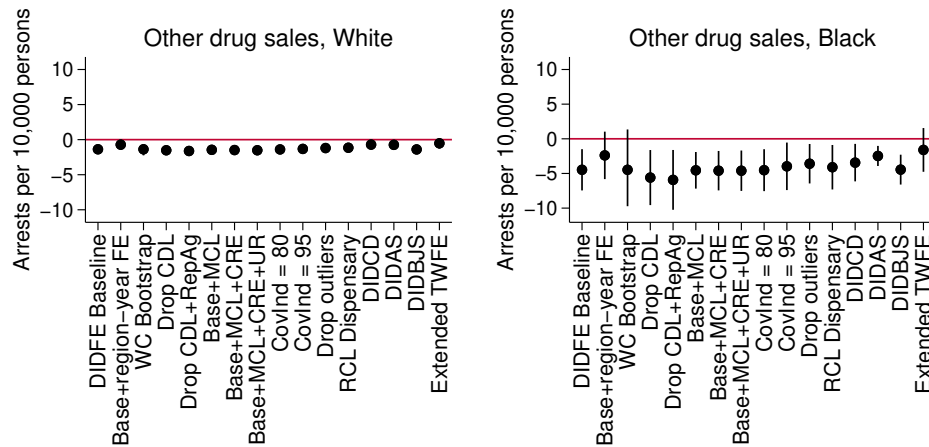


Figure S28: Other drug sales arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

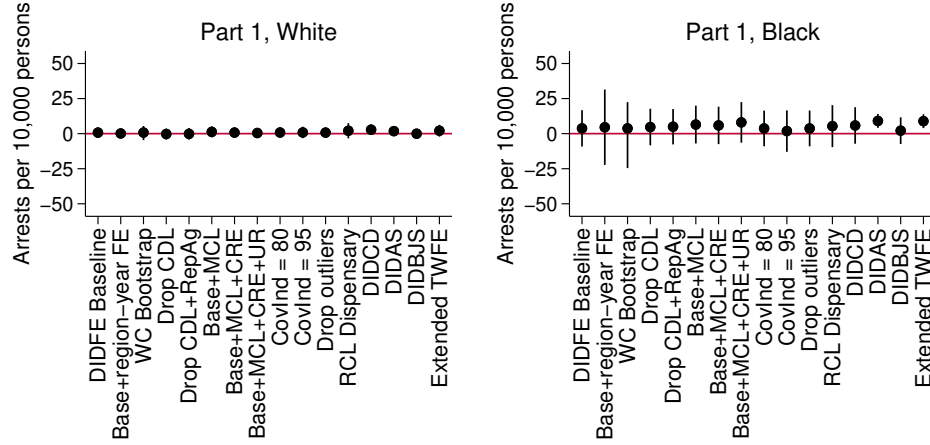


Figure S29: Part 1 arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

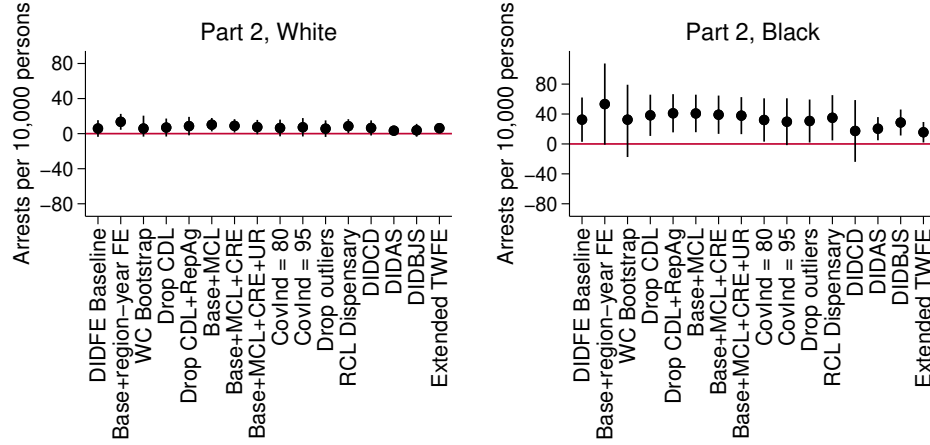


Figure S30: Part 2 arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

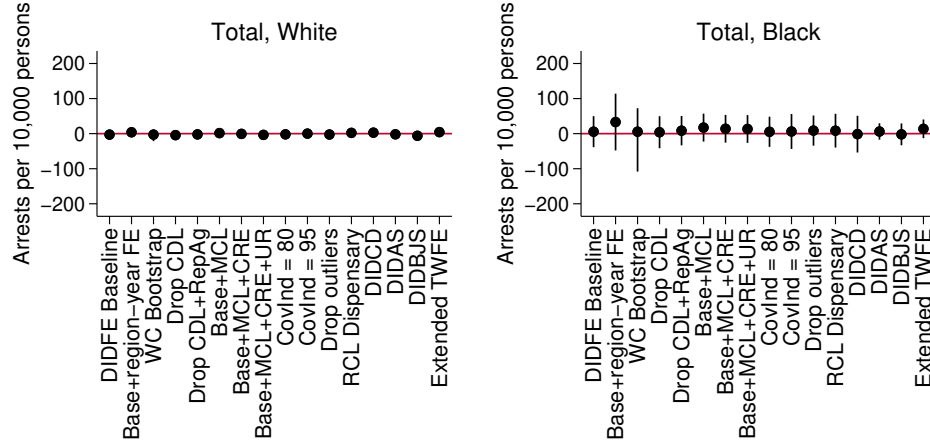


Figure S31: Total arrest rates, robustness checks

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. DIDFE Baseline is the main specification. Region-year FE denote indicators for each US Census region interacted with each calendar year. WC Bootstrap calculates wild cluster bootstrap standard errors. Controls that are added or dropped include cannabis decriminalization laws (CDL), the number of reporting agencies (RepAg), medical cannabis laws (MCL), criminal record expungement laws (CRE), and the unemployment rate (UR). Sample is restricted to counties with an agency reporting coverage threshold (CovInd) $\geq 65\%$ unless otherwise noted. Outliers are arrest rates above 2 standard deviations from the county-level mean. RCL dispensary replaces the RCL indicator with an indicator for recreational cannabis dispensary laws. DIDCD implements the multiperiod DID estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS shows the interaction weighted DID estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. DIDBJS shows the imputation approach of [Borusyak et al. \(2023\)](#). Extended DID shows the extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach.

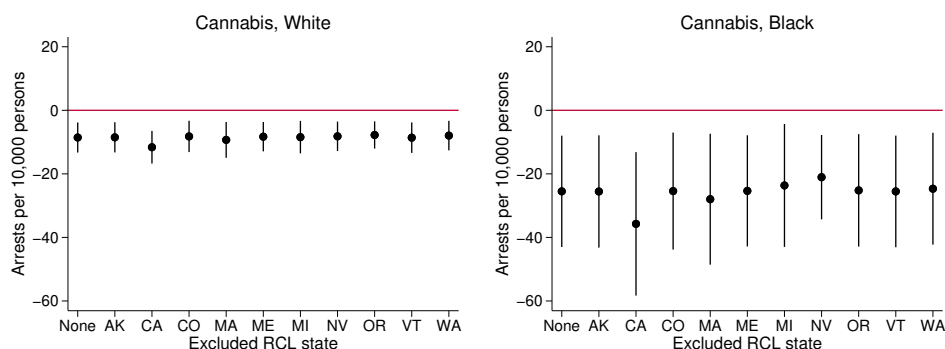


Figure S32: Cannabis arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

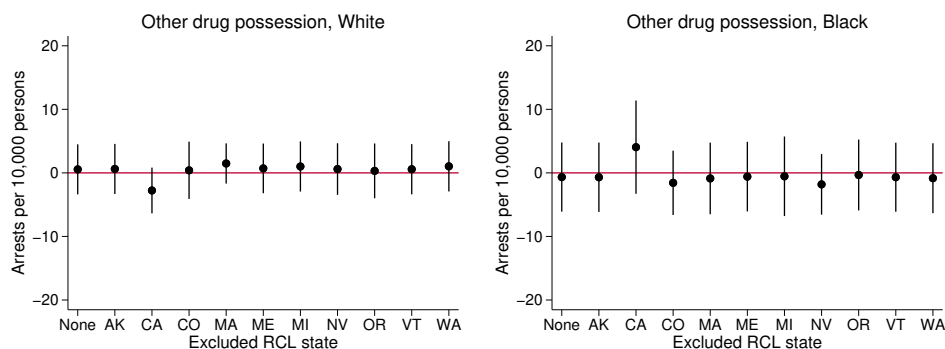


Figure S33: Other drug possession arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

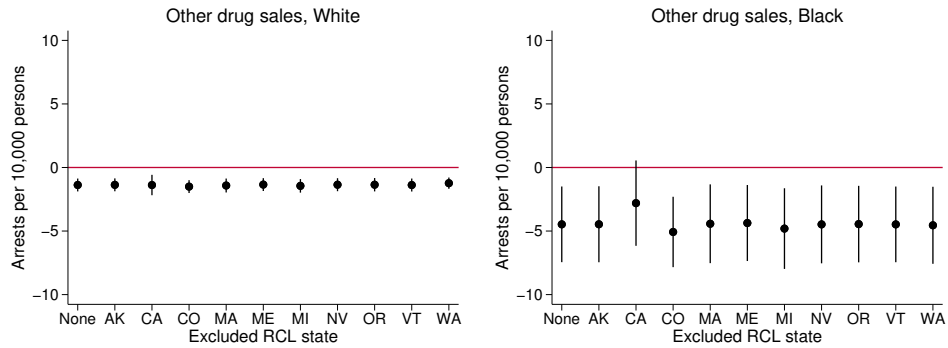


Figure S34: Other drug sales arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

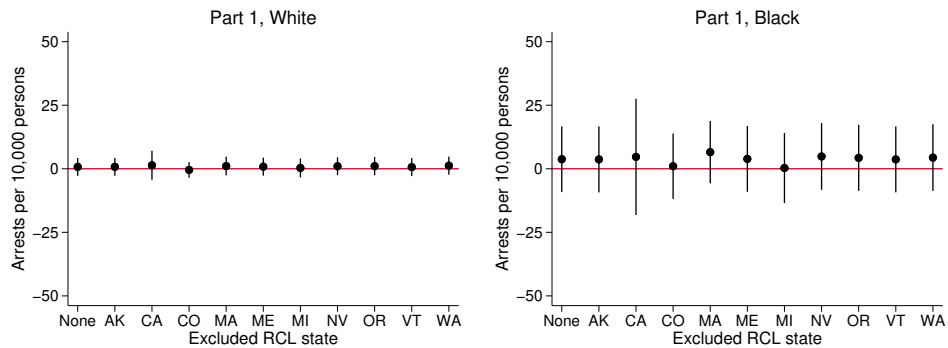


Figure S35: Part 1 arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

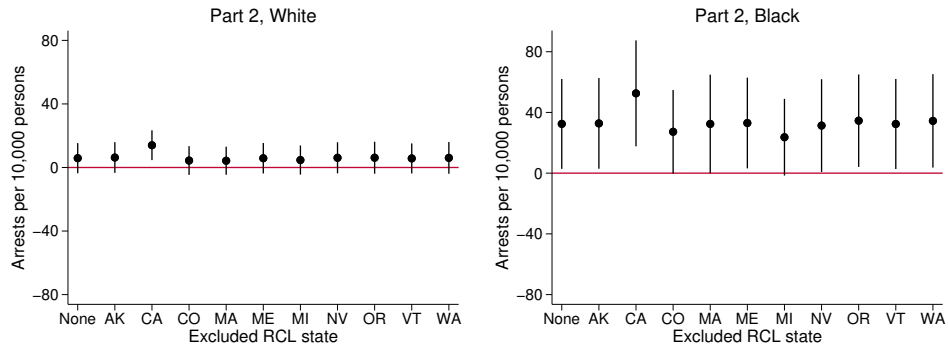


Figure S36: Part 2 arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

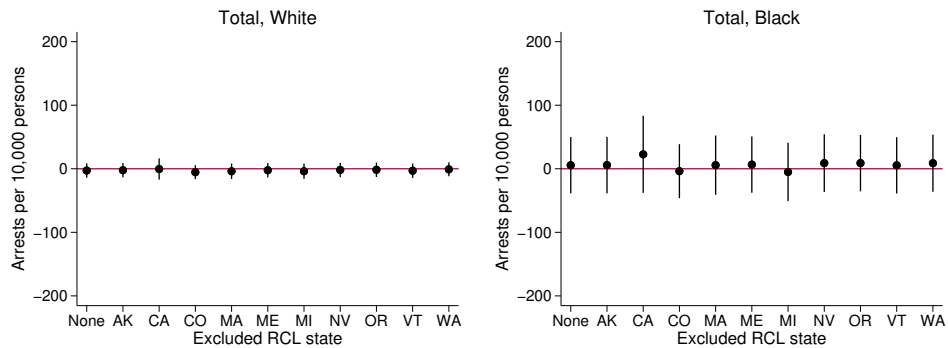


Figure S37: Total arrest rates, leave-one-out robustness

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient corresponds to a separate two-way fixed effects regression (see Equation 1). Bars denote 95% confidence intervals from standard errors clustered at the state level. Each regression excludes one RCL state at a time.

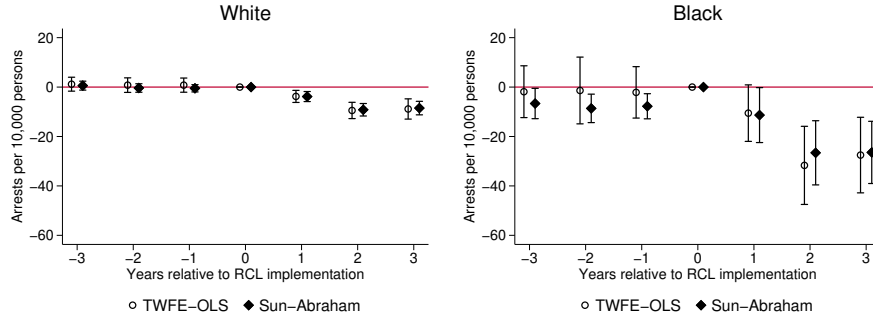


Figure S38: Cannabis arrest rates, alternative DID estimator

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Hollow markers correspond to the standard two-way fixed effects OLS estimator. Solid markers show the interaction-weighted estimator proposed in [Sun and Abraham \(2021\)](#). Bars denote 95% confidence intervals from robust standard errors clustered at the county level. Controls include the number of reporting agencies and cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

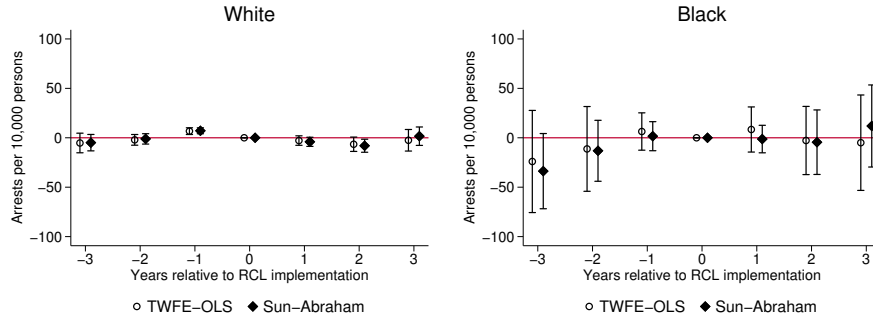


Figure S39: Total arrest rates, alternative DID estimator

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Counts for a given outcome are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Hollow markers correspond to the standard two-way fixed effects OLS estimator. Solid markers show the interaction-weighted estimator proposed in [Sun and Abraham \(2021\)](#). Bars denote 95% confidence intervals from robust standard errors clustered at the county level. Controls include the number of reporting agencies and cannabis decriminalization laws. The reference year is $t = 0$, the year immediately before RCL implementation. RCL=Recreational cannabis laws.

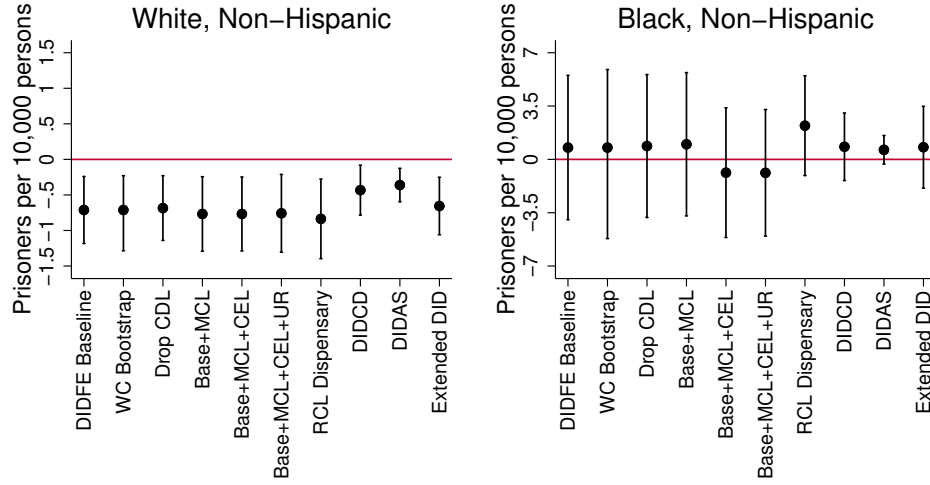


Figure S40: Prison admissions for drug-defined offenses, robustness checks

Notes: Prison admissions data are from the 2007-2019 National Corrections Reporting Program. The unit of analysis is a state-year. Counts for a given racial group are divided by state-year population estimates corresponding to that racial group, and multiplied by 10,000. Each coefficient is based on separate two-way fixed effects regressions (see Equation 1). Regressions are weighted by race-specific population. All regressions include state and year fixed effects, and control for CDLs unless stated otherwise. DIDFE=Two-way fixed effect difference-in-differences estimator. DIDCD=Multi-period difference-in-differences estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS=Interaction weighted difference-in-differences estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. Extended DID=Extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach. WC Bootstrap=Wild cluster bootstrap. RCL=Recreational cannabis laws. MCL=Medical cannabis laws. CDL=Cannabis decriminalization laws. CEL=Cannabis record expungement laws. UR=Unemployment rate.

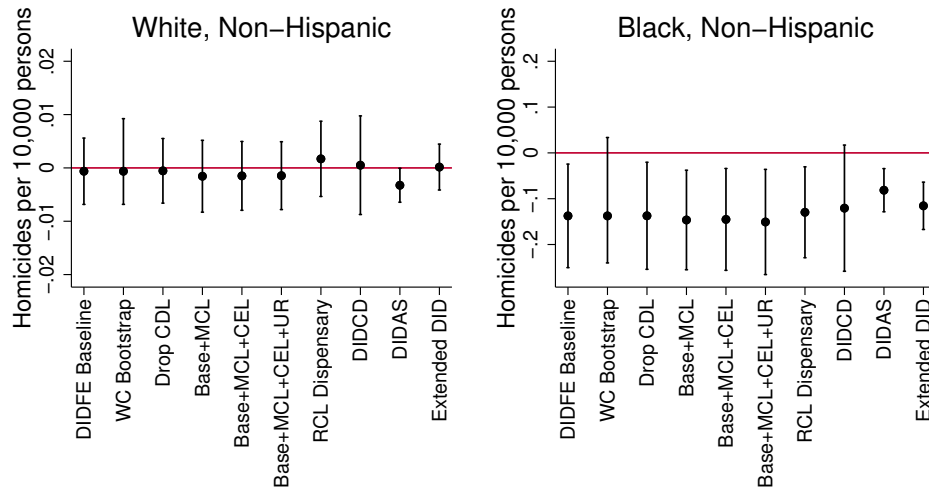


Figure S41: Homicides with gun injury, robustness checks

Notes: Homicide data are from the 2007-2019 NVSS Mortality Files. The unit of analysis is a state-year-quarter. Counts for a given racial group are divided by state-year population estimates corresponding to that racial group, and multiplied by 10,000. Each coefficient is based on separate two-way fixed effects regressions (see Equation 1). Regressions are weighted by race-specific population. All regressions include state and year-quarter fixed effects, and control for CDLs unless stated otherwise. DIDFE=Two-way fixed effect difference-in-differences estimator. DIDCD=Multi-period difference-in-differences estimator described in [De Chaisemartin and d'Haultfoeuille \(2024\)](#) capturing the average effect in the first three years post RCLs. DIDAS=Interaction weighted difference-in-differences estimator described in [Sun and Abraham \(2021\)](#) capturing the average effect in the first three years post RCLs. Extended DID=Extended TWFE estimator proposed in [Wooldridge \(2021\)](#), using the Mundlak approach. WC Bootstrap=Wild cluster bootstrap. RCL=Recreational cannabis laws. MCL=Medical cannabis laws. CDL=Cannabis decriminalization laws. CEL=Cannabis record expungement laws. UR=Unemployment rate.

E Arrests by Offense Categories

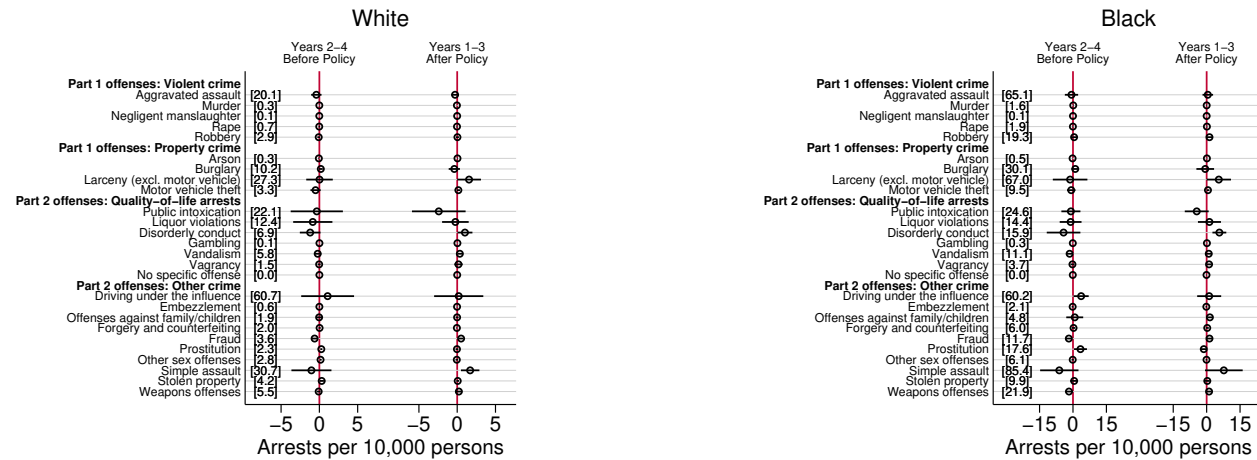


Figure S42: Arrest rates, by offense categories

Notes: Arrest data are from the 2007-2019 Uniform Crime Reports Arrests by Age, Sex, and Race, restricting to adults only. The unit of analysis is a county-year. Effect of recreational cannabis laws on arrest rates for all crime categories, by race groups (White and Black). Counts for a given race are divided by county-year population estimates corresponding to that race and multiplied by 10,000. Sample restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Coefficients and 95% confidence intervals shown from standard errors clustered by state. Numbers in brackets on the left show the pre-policy mean in RCL states. Each pair of coefficients (for a given offense and race group) is based on separate two-way fixed effects regression, with an indicator for years 2 to 4 prior to the policy and years 1 to 3 after the policy (the reference period is the year prior to RCL). Regressions are weighted by race-specific population. All regressions include county and year fixed effects. Control variables include the number of reporting agencies and cannabis decriminalization laws. RCL=Recreational cannabis laws.

F Potential Mechanisms

F.1 Police Officers

Table S6: Effect of recreational cannabis laws on police officers

	Sworn officers		Civil officers		Total officers	
RCL	0.18		0.15**		0.33**	
	(0.12)		(0.06)		(0.16)	
RCL Dispensary	0.15		0.16**		0.31	
	(0.14)		(0.06)		(0.19)	
Mean	3.63	3.60	0.93	0.92	4.56	4.52
N	4097	4097	4097	4097	4097	4097

Notes: Police officer counts are from the 2007-2019 LEOKA. County-year counts are divided by county-year population estimates, and multiplied by 10,000. Sample is restricted to counties with an agency reporting coverage threshold $\geq 65\%$. Each coefficient is based on a separate two-way fixed effects regression (Equation 1). Regressions are weighted by total population estimates. All regressions include county and year fixed effects. Controls include the number of reporting agencies and cannabis decriminalization laws. Standard errors clustered by state are in parentheses. The pre-policy outcome mean is reported for RCL states. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

F.2 Criminal Activity

F.2.1 Data

We describe incident data on calls for service and reported crimes to police in select RCL cities. Los Angeles, Denver, District of Columbia, and Boston reflect reported crimes to police. Portland (C, E, NE), Seattle (CI, E, NE), Burlington (CI, E, NE), Detroit (CI, E), and Sacramento (CI, PI, E, NE) reflect calls for service, and include the types of calls in parentheses. CI=Civilian initiated calls for service to police. PI=Police initiated calls for service. E=Emergency calls for service. NE=Non-emergency calls for service.

Portland, OR. We analyzed 2012-2019 civilian initiated calls for service collected by the Portland Police Bureau, which included calls to the emergency 911 line or the non-emergency line.¹ The Portland Police Bureau counted all calls for service where at least one Portland police officer was dispatched. Final

¹<https://public.tableau.com/app/profile/portlandpolicebureau/viz/DispatchedCallsforService/DispatchedCalls>

call type was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge calls with 2012 population data at the tract level. Calls deemed sensitive due to the nature of the incident, potential suspect or offender, potential victim-offender relationship, or investigation were not included in the public data. Latitude and longitude information for sensitive incidents (i.e., domestic violence, rape, child abuse, restraining order, behavioral health) were not reported in the public data and therefore not reflected in our neighborhood analyses. Drug-defined offenses are included along with other vice crimes under the offense description “Vice.” We therefore use this offense description to measure drug-defined offenses.

Seattle, WA. We analyzed 2010-2019 civilian initiated calls for service collected by the Seattle Police Department, which included calls to the emergency 911 line and the non-emergency line.² Data only contained records of police response. If a call was queued in the system but cleared before an officer could respond, it was not included. While data included police initiated calls for service, these were inadequately reported for many types of calls during the study period, and thus, we excluded them from the analyses. Final call type was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge calls with 2010 population data at the tract level.

Burlington, VT. We analyzed 2012-2019 civilian initiated calls for service collected by the Burlington Police Department, which included calls to the emergency 911 line or the non-emergency line. Data also included other incidents collected through online reports, in person, or initiated by police.³ While data included police initiated calls for service, these were inadequately reported for many types of calls during the study period, and thus, we excluded them from the analyses. Call type was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge calls with 2012 population data at the tract level. Latitude and longitude information for sensitive incidents (i.e., domestic violence, juvenile problem) were not reported in the public data and therefore not reflected in our neighborhood analyses.

Detroit, MI. We analyzed 2017-2019 civilian initiated calls for service collected by the Detroit Police Department, which included emergency calls to the 911 line but did not include non-emergency calls.⁴ While data included

²<https://data.seattle.gov/Public-Safety/Call-Data/33kz-ixgy>

³<https://data.burlingtonvt.gov/search?collection=Dataset&q=incident>

⁴<https://data.detroitmi.gov/datasets/detroitmi::911-calls-for-service/about>

police initiated calls for service, these were inadequately reported for many types of calls during the study period, and thus, we excluded them from the analyses. Call description was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge calls with 2017 population data at the tract level.

Sacramento, CA. We analyzed 2014-2019 civilian and police initiated calls for service collected by the Sacramento Police Department, which included calls to the emergency 911 line or the non-emergency line.⁵ The data included calls for service that were entered into the computer-aided dispatch system, regardless of whether police responded to the call. Civilian calls cannot be separately identified from police calls in the data, and thus estimates are based on the combined data. Call description was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge calls with 2014 population data at the tract level. Latitude and longitude for sensitive cases (i.e. domestic violence, rape, child abuse, behavioral health) were not reported in the public data.

Washington, DC. We analyzed 2010-2019 crime reports collected by the District of Columbia Metropolitan Police Department.⁶ The dataset contains a subset of locations and attributes of incidents reported in the Analytical Services Application crime report database by the District of Columbia Metropolitan Police Department. This data is shared via an automated process where addresses are geocoded to the District's Master Address Repository and assigned to the appropriate street block. Only Part 1 offenses are collected, and thus, we were not able to analyze Part 2 offenses. Latitude and longitude were used to merge calls with 2010 population data at the tract level.

Los Angeles, CA. We analyzed 2010-2019 crime reports collected by the Los Angeles Police Department, which included index crimes, select Part 2 crimes, and race of victim.⁷ This data was transcribed from original crime reports that were typed on paper and therefore there may be some inaccuracies within the data. Tracts primarily in two areas, Olympic and Topanga, did not report crimes in 2014. We imputed 2014 values with the average number of reported crimes in 2013 and 2015 for these tracts. Crime type was used to

⁵<https://data.cityofsacramento.org>

⁶<https://opendata.dc.gov/datasets>

⁷<https://data.lacity.org/Public-Safety/Crime-Data-from-2010-to-2019/63jg-8b9z>

categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge crimes with 2010 population data at the tract level.

Denver, CO. We analyzed 2010-2019 crime reports collected by the Denver Police Department, which included Part 1 crimes and select Part 2 crimes.⁸ The data is based on the National Incident Based Reporting System (NIBRS) which includes all victims of person crimes and all crimes within an incident. The data is dynamic, which allows for additions, deletions and/or modifications at any time, resulting in more accurate information in the database. Due to continuous data entry, the number of records in subsequent extractions are subject to change. In accordance with legal restrictions against identifying sexual assault and child abuse victims and juvenile perpetrators, victims, and witnesses of certain crimes, public data takes the following precautionary measures: (a) Latitude and longitude of sexual assaults are not included. (b) Child abuse cases, and other crimes which by their nature involve juveniles, or which the reports indicate involve juveniles as victims, suspects, or witnesses, are not reported at all. Crimes that are initially reported, but that are later determined not to have occurred, are called “unfounded” offenses. These incidents are excluded once they have been designated as unfounded. Most Part 2 offenses were not properly reported until 2013. Therefore, we only analyzed a small number of Part 2 offenses that were being reported prior to 2012. Crime type was used to categorize Part 1 offenses, and latitude and longitude were used to merge calls with 2010 population data at the tract level.

Boston, MA. We analyzed 2015-2019 crime reports collected by the Boston Police Department, which included Part 1 crimes and select Part 2 crimes.⁹ Full data reporting is available starting in Q3/2015 and document the initial details surrounding an incident to which the Boston Police Department respond. We dropped Q4/2019 due to a sharp decline in data reporting. Crime type was used to categorize Part 1 and Part 2 offenses, and latitude and longitude were used to merge crimes with 2015 population data at the tract level.

F.2.2 Outcome Measures

Calls for service and reported crime data identify incident type with names (i.e. text). Incidents reported and names used vary across cities, which creates challenges for categorizing incidents using a standard and consistent methodology. To match incident definitions in call and crime data to definitions in

⁸<https://www.denvergov.org/opendata/dataset/city-and-county-of-denver-crime>

⁹<https://data.boston.gov/dataset/crime-incident-reports-august-2015-to-date-source-new-system>

arrest and incarceration data as much as possible, we categorize drug-defined offenses and other offenses as follows.

Drug-defined offenses. Incidents with text indicating drug possession, drug sales, narcotic violations, or drug violations. Drug overdoses and drug intoxication were not included in this category.

Other offenses. Incidents with text indicating Part 1 and Part 2 offenses. Part 1 offenses can include violent (homicide, murder, manslaughter, rape, sexual assault, aggravated or felonious assault, and robbery) and property crimes (burglary, theft, larceny, motor vehicle theft, and arson). Part 2 offenses include financial and other white collar crimes (fraud, embezzlement, forgery, identity theft, blackmail, bribery, money laundering, scam), simple assault (simple assault, threats, harassment, fight, battery), vandalism (vandalism, graffiti, malicious destruction of property), other theft (possession of stolen property, property missing, lost or found), public intoxication (intoxication, drunkenness, drug overdose), driving under the influence, gambling, liquor violations, public disorder (disorder, disturbance, trespassing, mischief, nuisance, noise, unwanted person, annoyance, stalking, verbal dispute, panhandling, loitering), weapon offenses (weapon, armed, knife, gun, shots fired), and other sex offenses (prostitution, indecent exposure, pornography, sexual harassment, lascivious acts, etc). We drop all incidents of domestic violence and child maltreatment regardless of offense category because coordinates are often missing in most cities to protect victims.

Uncategorized. Across cities, we encounter incidents with some variation of the following names: “suspicious (person, circumstance, auto, building)” or “investigate (person, auto, building).” These incidents have high frequency in many cities, but it is unclear whether all or some can be considered either Part 2 offenses, an alternative name for incidents related to “premise checks” or “welfare checks,” or some catch all general category. We therefore do not include these incidents in the definition of Part 2 offenses, but report estimates for “suspicious event” in Table S8, defined as suspicious person, circumstance, auto or investigate person or auto.

F.2.3 Minority Neighborhoods

Histograms in Figure S43 depict the distribution of Census tracts based on the proportion of Hispanic and non-Hispanic Black residents b in the tract. The red line indicates the threshold m used to classify tracts as minority

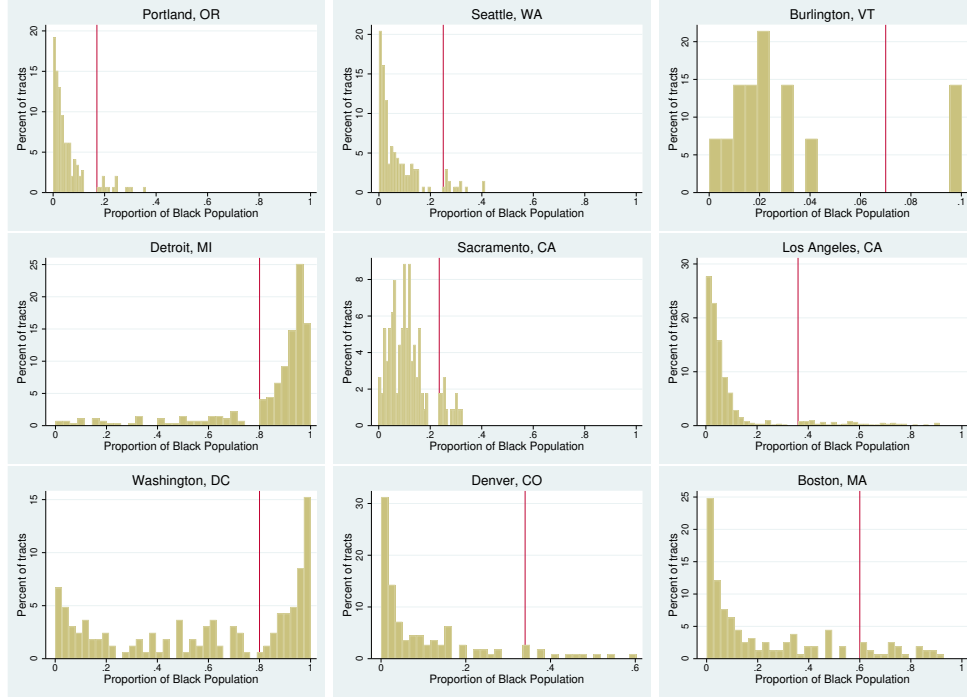


Figure S43: Distribution of minority neighborhoods

neighborhoods, with all tracts where the proportion of Black residents b is greater or equal than m classified as minority areas ($b \geq m$). The distribution of tracts varied widely across cities, making it challenging to apply a common threshold m for all cities. We therefore implemented a tailored approach that accounted for these differences in distribution across cities.

In cities where a majority of tracts had a low proportion of Black residents (e.g., Portland, Seattle, Sacramento, Los Angeles, Denver, Boston, Burlington), we used modified percentile-based cutoffs. In these cases, we classified tracts as minority neighborhoods if its proportion of Black residents was approximately at the 90th percentile or higher ($m \approx b_{90th}$). Specific assignment varied slightly from the 90th percentile based on histogram patterns and plausible natural breaks. In cities where a substantial number of tracts had a high proportion of Black residents (Detroit, District of Columbia), we classified tracts as minority neighborhoods if the proportion of Black persons b was at least 0.80 ($m = 0.80$), regardless of percentile. We then established a comparison group threshold n to classify tracts as non-minority neighborhoods with $b \leq n$. We set $n = m - a$, effectively excluding tracts that were adjacent but

below threshold m if the proportion of Black persons b fell within $[m - a, m)$. We defined the adjacent tract threshold as $a = 0.05$. We did this to exclude tracts that would otherwise be classified as non-minority neighborhoods despite having a proportion of Black residents b close to the threshold m for minority neighborhoods.

F.2.4 Robustness Checks and Additional Findings

Robustness Checks. Table S7 examines the robustness of our baseline estimates in Table 4 to alternative approaches for classifying tracts into minority and non-minority neighborhoods. We show ten exercises. (i) We start by reporting baseline estimates, where the minority tract threshold m was generated with the tailored approach previously described in F.2.3 and S43 and the adjacent tract threshold $a = 0.05$. We then conduct various exercises, modifying thresholds for minority tracts m , non-minority tracts n , or adjacent tracts a .

In the first set of exercises, we modify the adjacent tract threshold a , while fixing m as defined at baseline. (ii) We set $a = 0$ to reintroduce the previously excluded adjacent tracts (those within 5 percentage points below the city-specific threshold m). (iii) We also set $a = 0.10$, which excludes a larger number of adjacent tracts than the baseline specification.

For the second set of exercises, we modify the treatment tract threshold m by using city-specific percentiles, while fixing $a = 0.05$ as defined at baseline. (iv-vi) We assign threshold m using a strict percentile-based approach (85th, 90th, 95th percentile) that classifies a fixed percentage of tracts as minority neighborhoods in each city ($m = b_{85th}$, $m = b_{90th}$, $m = b_{95th}$), irrespective of the shape of the distribution. (vii) We assign threshold m using an alternative tailored approach with two different conditions for m , where a tract is considered a minority neighborhood if the proportion of Black residents b is greater than the minimum between $m = b_{90th}$ or $m = 0.50$, so that cities that are more diverse rely on the 50% threshold instead of the percentile ($m = \min\{b_{90th}, 0.5\}$).

For the last set of exercises, we use a relative deviation approach, defining tracts as minority neighborhoods if its proportion of Black persons b exceeds the citywide average $\bar{b}$ by k times the citywide standard deviation $sd(b)$. Again, we hold the adjacent tracts that are excluded fixed at $a = 0.05$. (viii-ix) We classify tracts as minority neighborhoods if b is higher than the citywide average plus 1 or 2 standard deviations ($m = \bar{b} + 1sd(b)$, $m = \bar{b} + 2sd(b)$). (x) Lastly, we modify this approach by applying a similar rule for the non-minority tracts. To avoid losing too many tracts, we use half a standard deviation in

our definition so that the threshold for belonging to the non-minority group is $n = \bar{b} - 0.5sd(b)$ and the threshold for belonging to the minority group is $m = \bar{b} + 0.5sd(b)$, with all other tracts in the middle excluded.

Additional Findings. We stratify Part 2 offenses in Table [S8](#) and find heterogeneity across offenses and cities.

Table S7: Alternative classification of minority neighborhoods

	Drug-defined offenses	Other offenses		Net effects	
		Part 1			
		Violent	Property	Part 2	Total
Baseline	-1.39*** (0.29)	-0.57 (0.36)	-2.48*** (0.79)	-1.89 (1.84)	-4.80** (2.05)
Mean	3.12	15.62	31.15	78.63	106.53
$a = 0$	-1.22*** (0.29)	-0.53 (0.35)	-2.47*** (0.77)	-1.49 (1.79)	-4.40** (1.99)
Mean	3.12	15.62	31.15	78.63	106.53
$a = 0.10$	-1.39*** (0.30)	-0.55 (0.36)	-2.43*** (0.81)	-2.07 (1.84)	-4.83** (2.09)
Mean	3.12	15.62	31.15	78.63	106.53
$m = b_{85th}$	-1.04*** (0.32)	0.28 (0.38)	-0.97 (0.84)	1.24 (2.50)	0.12 (2.83)
Mean	4.45	12.59	33.48	60.95	100.47
$m = b_{90th}$	-1.49*** (0.32)	-0.44 (0.43)	-2.47** (1.00)	-1.65 (1.97)	-4.78* (2.67)
Mean	4.52	13.70	34.69	63.10	104.84
$m = b_{95th}$	-1.86*** (0.51)	-0.61 (0.59)	-3.40*** (1.26)	-2.74 (2.50)	-6.88** (3.41)
Mean	4.56	13.96	34.79	61.86	104.06
$m = \min\{b_{90th}, 0.5\}$	-1.30*** (0.42)	-0.39 (0.37)	-1.51* (0.86)	-1.82 (1.93)	-3.52** (2.16)
Mean	3.05	15.03	30.96	79.23	99.60
$m = b + 1sd(b)$	-1.18*** (0.41)	-0.31 (0.35)	-2.20** (0.89)	-2.48 (1.97)	-4.68** (2.21)
Mean	5.12	12.56	34.27	59.23	91.19
$m = b + 2sd(b)$	-2.19*** (0.52)	-0.36 (0.75)	-3.62*** (1.27)	-2.55 (2.58)	-7.14* (3.89)
Mean	5.81	13.74	37.51	60.26	112.61
$n = b - .5sd(b),$ $m = \bar{b} + .5sd(b)$	-0.88*** (0.30)	0.06 (0.33)	-0.19 (0.81)	1.30 (2.43)	0.65 (2.60)
Mean	3.85	13.92	33.76	75.65	105.67

Notes: Calls for service and reported crime data in select RCL cities, pooling all nine cities. Tract-year-quarter incident counts are stratified by minority neighborhoods using different definitions. m = minority neighborhood threshold. n = non-minority neighborhood threshold. a = adjacent tract threshold. b = proportion of Black residents in tract. $\bar{b}$ = citywide average of b . $sd(b)$ = citywide standard deviation of b . Standard errors clustered at the tract level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S8: Effect of recreational cannabis laws on Part 2 offenses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Part 2 Offenses							Related Incidents	
	Financial	Weapon	Simple Assault	Vandalism	Disorder	Public Intoxic.	DUI	Other Part 2	Suspicious Event
Pooled	-0.62*** (0.16)	-0.21 (0.31)	-1.42*** (0.42)	0.33** (0.16)	-1.38 (2.50)	1.29 (0.87)	0.57** (0.23)	0.32 (0.33)	-0.96 (2.31)
Mean	3.60	12.40	19.09	6.84	55.62	7.97	5.71	3.14	26.86
Portland, OR	-0.02 (0.23)	-0.61 (0.38)	-0.72 (0.64)	-0.67 (0.43)	-12.52* (6.45)	n.a. n.a.	0.03 (0.12)	n.a. n.a.	-2.84 (1.81)
Mean	1.78	4.90	14.09	6.71	80.45	n.a.	0.76	n.a.	22.65
Seattle, WA	-0.29 (0.45)	-0.41 (0.35)	-0.32 (0.52)	-0.01 (0.37)	-9.52 (7.87)	3.53 (2.81)	0.51*** (0.16)	2.61 (2.86)	-12.11*** (2.97)
Mean	5.38	3.11	3.21	10.02	89.00	5.58	1.25	9.42	56.08
Burlington, VT	0.46 (0.53)	n.a. n.a.	-0.20 (2.06)	2.32 (2.32)	15.46 (16.40)	11.42 (14.43)	0.25* (0.12)	0.60 (2.22)	14.13 (8.20)
Mean	8.83	n.a.	36.90	24.46	149.15	55.73	1.88	67.40	102.33
Detroit, MI	-0.30** (0.14)	0.42 (0.81)	-3.65** (1.54)	0.57 (0.35)	3.66 (2.76)	0.23 (0.54)	1.42** (0.72)	0.13 (0.24)	2.30 (1.47)
Mean	0.77	15.36	27.92	5.66	46.45	7.19	7.34	1.59	13.73
Sacramento, CA	n.a. n.a.	-2.13 (1.43)	-1.37 (1.60)	1.13* (0.63)	10.20 (10.94)	-0.35 (0.77)	-0.02 (0.14)	-0.69 (0.61)	6.73 (13.61)
Mean	n.a.	18.42	30.12	5.49	116.48	7.27	2.08	4.91	118.45
Los Angeles, CA	-1.00*** (0.26)	n.a. n.a.	-1.69** (0.74)	0.61** (0.28)	n.a. n.a.	n.a. n.a.	n.a. n.a.	0.23 (0.20)	n.a. n.a.
Mean	5.85	n.a.	12.57	7.16	n.a.	n.a.	n.a.	1.66	n.a.
Boston, MA	-0.94** (0.39)	-0.58** (0.28)	0.66 (0.76)	-0.90 (0.56)	2.13*** (0.52)	0.51* (0.26)	n.a. n.a.	0.47 (0.43)	2.04*** (0.69)
Mean	7.72	3.91	23.12	13.96	18.42	1.02	n.a.	8.32	12.68
Denver, CO	0.14 (0.80)	1.51** (0.68)	-0.68 (0.90)	0.23 (0.19)	0.09 (0.47)	n.a. n.a.	n.a. n.a.	-0.87* (0.46)	n.a. n.a.
Mean	2.58	1.83	3.05	0.94	8.64	n.a.	n.a.	0.38	n.a.

Notes: Calls for service or reported crime data for Part 2 offenses and other incidents that are not in the Part 2 definition but that might be related. Portland (C, E, NE), Seattle (CI, E, NE), Burlington (CI, E, NE), Detroit (CI, E), and Sacramento (CI, PI, E, NE) reflect calls for service. Los Angeles, Denver, DC, and Boston reflect reported crimes. DC does not report Part 2 offenses. Outcomes reflect total incident counts for Part 2 offenses in a tract-quarter, stratified by minority neighborhoods. Due to differences in collection and reporting of incidents, outcomes can be inconsistent across cities. Details in Sections 2 and F.2. CI=Civilian initiated calls for service. PI=Police initiated calls for service. E=Emergency calls for service. NE=Non-emergency calls for service. Standard errors clustered at the tract level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F.3 DUI Fatalities

We examine the effect of RCLs on DUI fatalities per 10,000 people using data from the Fatality Analysis Reporting System (FARS), which provides a comprehensive record of fatal motor vehicle traffic crashes. This dataset includes all public road accidents where at least one person died within 30 days of the crash. While FARS data are available in 2007, changes in some variables make earlier years not directly comparable with later data. Therefore, we focus on the period from 2008 to 2019.

We aggregate deaths at the state-year level, distinguishing between White and Black individuals (excluding other races or cases with unidentified race). We identify accidents where drivers were suspected or confirmed to be under the influence of drugs (excluding alcohol and nicotine) based on police reports and/or drug tests. We convert fatalities to rates per 10,000 people, and we perform data checks to address inconsistencies, such as excluding Pennsylvania due to having zero fatalities in most years of this sample.

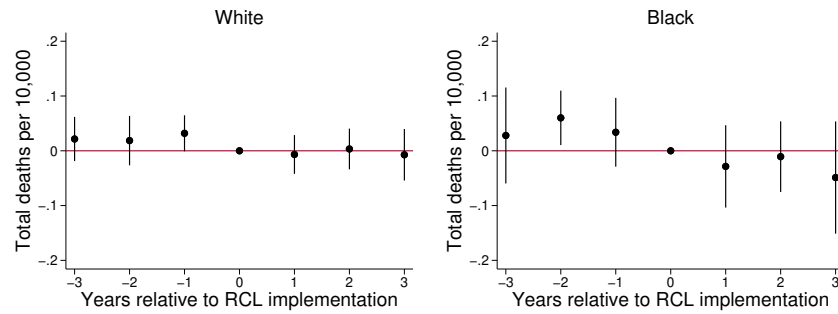


Figure S44: DUI fatality rates, event study

Notes: DUI fatality rates are from the 2008-19 Fatality Analysis Reporting System. State-year counts for a given race are divided by state-year population estimates corresponding to that race, and multiplied by 10,000. Event study regressions are weighted by race-specific population estimates. Controls include cannabis decriminalization laws. 95% confidence intervals are clustered at the state level. The reference year is $t = 0$, the year immediately before RCL implementation.

References

- Borusyak, K., X. Jaravel, and J. Spiess (2023). Revisiting event study designs: Robust and efficient estimation. *Review of Economic Studies*.
- Clarke, D., J. P. Romano, and M. Wolf (2020). The Romano–Wolf multiple-hypothesis correction in Stata. *The Stata Journal* 20(4), 812–843.
- De Chaisemartin, C. and X. d’Haultfoeuille (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* 110(9), 2964–96.
- De Chaisemartin, C. and X. d’Haultfoeuille (2024). Difference-in-differences estimators of intertemporal treatment effects. *REStat*, 1–45.
- Edwards, E., E. Greytak, B. Madubonwu, T. Sanchez, S. Beiers, C. Resing, P. Fernandez, and S. Galai (2020). A tale of two countries: Racially targeted arrests in the era of marijuana reform. *ACLU*.
- Grucza, R. A., M. Vuolo, M. J. Krauss, A. D. Plunk, A. Agrawal, F. J. Chaloupka, and L. J. Bierut (2018). Cannabis decriminalization: A study of recent policy change in five US states. *International Journal of Drug Policy* 59, 67–75.
- Gunadi, C. and Y. Shi (2022). Cannabis decriminalization and racial disparity in arrests for cannabis possession. *Social Science & Medicine* 293, 114672.
- Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics*, 65–70.
- NORML (2022). State expungement laws. <https://norml.org/laws/expungement/>.
- ProCon (2022). State-by-state recreational marijuana laws. *ProCon.org*.
- RAND (2020). Optic vetted medical marijuana policy data. Technical report, RAND-USC Schaeffer Opioid Policy Tools and Information Center.
- Romano, J. P. and M. Wolf (2005). Stepwise multiple testing as formalized data snooping. *Econometrica* 73(4), 1237–1282.
- Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* 225(2), 175–199.

Wooldridge, J. M. (2021). Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators. Technical report, Available at SSRN 3906345.