The Effect of Criminal Justice Decisions on Community Safety

Greg DeAngelo

Claremont Graduate University
Department of Economic Sciences
Computational Justice Lab - Director & Founder
www.computationaljusticelab.org

November 18, 2020

Overview

Overview - Police Use of Force

Concerns regarding officer conduct have received considerable recent attention.

Notable deaths at the hands of law enforcement:

- Eric Garner - NYPD
- Michael Brown - Ferguson PD
- Tamir Rice - Cleveland PD
- Freddie Gray - Baltimore PD
- George Floyd - Minneapolis PD

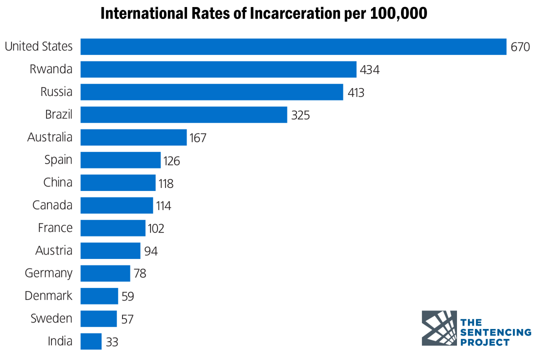
Response: Declarations of racism as a public health crisis (San Bernardino, Riverside)

Overview - Prosecutor Discretion

- Is prosecutor discretion a regrettable artifact of scarcity?
  - If court dockets and jails/prisons were sufficiently spacious, could we just do away with prosecutor discretion?
  - Likely answer: no!
- Some countries and states require prosecutors to pursue all charges for which they have enough evidence to return a guilty verdict
  - Some states even allow victims to bring cases when prosecutors decide not to do so
- We endow judges and juries with with considerable discretion, and perhaps should give them even more
  - But, prosecutor discretion provides an opportunity to enhance efficiency
    - Example: School has zero tolerance rules for weapons. Student brings birthday cake with knife to cut cake to school. School suspends student for 45 days.

Overview - Incarceration

- The United States has the highest incarceration rate out of any industrialized county in the world.



- Elected officials often face demands from the public for criminal justice reform to solve the mass incarceration problem.

Does the Presence of Female and Minority Police Reduce the Use of Force?

Joint with Hunter Johnson - PhD student @ CGU

Motivation

- **Research Question:** To what extent can disparities in the likelihood of police use of force be explained by officer race and gender?
- **Motivation:**
  - We observe racial disparities in policing: Black citizens are proportionally over-represented in both arrests and use-of-force incidents
  - We want to know whether these disparities are attributable to statistical or taste-based discrimination
  - We are also interested in whether the presence of female officers affects the likelihood of force
- We examine Dallas Police Department (DPD) use-of-force incidents from 2014 – 2016

Table: Dallas Police Department

	Black	Hispanic	White	Male	Female	Total
Dallas Residents (2016)	310,099	530,277	373,197			1,277,445
Share	24.3%	41.5%	29.2%			
DPD Officers	893	706	1,736	2,845	604	3,449
Share	25.9%	20.5%	50.3%	82.5%	17.5%	
Arrests	19,160	10,654	8,607	30,794	7,980	38,783
Share	49.1%	27.3%	22.1%	79.4%	20.6%	
Use-of-Force Incidents	681	248	260	964	259	1,224
Share	55.6%	20.2%	21.2%	78.8%	21.2%	

- Our sample consists of nearly 38,000 911 service calls ending in arrest from 2014 through 2016
- Of these calls, 1,348 result in use of force (3.3%)
- Officers are assigned to 911 calls by dispatchers primarily on the basis of availability and proximity
- Using this sample, we avoid selection effects from officer-initiated interactions
- Officer race and gender should be exogenous in this sample conditional on call characteristics
- We use an IV approach with officer availability by race/gender as an instrument for whether an officer of a particular race/gender responds to a call

Data

- Data come from the Dallas Police Department for 2014 – 2016
- Dispatch Data
  - 1.4 million 911 calls identifying each dispatched officer
  - Contains detailed information on the nature of the 911 call, location, time, and which officers were involved, but does not contain civilian race or gender
- Arrest Data
  - Around 38,000 calls result in arrest
  - Contains arrest incidents with location, time, and civilian race and gender
- Use-of-Force Data
  - 1,348 calls result in force
  - Identifies the officers and civilians involved in force incidents as well as civilian demographics, location, time, and nature of force used
- Officer Data
  - Officer race, gender, age, and years of service by badge number

Data

- We rely on the set of 911 calls *resulting in arrest* rather than all 911 calls for two reasons:
    - Dispatch data do not contain civilian demographics; arrests and use-of-force data do
    - Arrests serve as a useful benchmark for scenarios that are likely to result in force
- The main sample contains 37,682 arrests, of which 1,348 (3.3%) result in force
- In attempting to replicate the results of Hoekstra & Sloan (2020), we use both the full sample of 1.4 million calls and the arrest sample

Table: Summary Statistics for All Samples

	All Calls		Arrest Sample		Force Sample	
	(1)		(2)		(3)	
Number of Calls	1,425,151		37,682		1,348	
Number of Arrests	37,682		37,682		1,232	
Proportion Resulting in Arrest	2.64%		100%		91.39%	
Number of Force Incidents	1,348		1,232		1,348	
Proportion Resulting in Force	0.09%		3.27%		100%	
Call-Level Variables						
Priority	2.64	(0.81)	2.19	(0.65)	1.96	(0.63)
Minutes Between Call and Dispatch	38.43	(77.45)	16.22	(33.21)	12.14	(33.09)
Day of Week						
Sunday	0.15	(0.36)	0.16	(0.36)	0.18	(0.39)
Monday	0.14	(0.35)	0.14	(0.35)	0.13	(0.34)
Tuesday	0.13	(0.34)	0.13	(0.34)	0.13	(0.34)
Wednesday	0.13	(0.34)	0.13	(0.33)	0.12	(0.33)
Thursday	0.14	(0.34)	0.14	(0.34)	0.11	(0.32)
Friday	0.15	(0.36)	0.15	(0.36)	0.14	(0.35)
Saturday	0.16	(0.36)	0.16	(0.37)	0.18	(0.38)
Watch						
8AM-4PM	0.33	(0.47)	0.28	(0.45)	0.2	(0.4)
4PM-12AM	0.42	(0.49)	0.42	(0.49)	0.42	(0.49)
12AM-8AM	0.25	(0.43)	0.3	(0.46)	0.38	(0.49)

Table: Summary Statistics for All Samples

	All Calls		**Arrest Sample**		**Force Sample**	
	(1)		(2)		(3)	
Number of Calls	1,425,151		37,682		1,348	
Number of Arrests	37,682		37,682		1,232	
Proportion Resulting in Arrest	2.64%		100%		91.39%	
Number of Force Incidents	1,348		1,232		1,348	
Proportion Resulting in Force	0.09%		3.27%		100%	
Call-Level Variables						
Black Officer Present	0.37	(0.48)	0.47	(0.5)	0.56	(0.5)
Hispanic Officer Present	0.32	(0.47)	0.47	(0.5)	0.59	(0.49)
White Officer Present	0.63	(0.48)	0.78	(0.42)	0.9	(0.31)
Male Officer Present	0.91	(0.28)	0.96	(0.19)	0.98	(0.13)
Female Officer Present	0.25	(0.43)	0.42	(0.49)	0.48	(0.5)
Officer Age	38.8	(8.3)	37.4	(6.6)	36.6	(5.3)
Officer Years of Service	11.5	(7.7)	10.1	(6)	9.6	(4.7)
Number of Officers Dispatched	2.21	(1.42)	4.1	(3.4)	7.04	(5.5)
Number of Officers Arrived	1.89	(1.16)	3.21	(2.49)	5.07	(4.02)
Civilian Characteristics						
Proportion Black Civilian	-	-	0.5	(0.5)	0.53	(0.5)
Proportion Hispanic Civilian	-	-	0.27	(0.44)	0.25	(0.43)
Proportion White Civilian	-	-	0.22	(0.41)	0.2	(0.4)
Proportion Male Civilian	-	-	0.8	(0.39)	0.82	(0.37)
Proportion Female Civilian	-	-	0.2	(0.39)	0.18	(0.37)
Civilian Age	-	-	35.1	(12.1)	31.9	(10.8)

Model & Results

- First, we model the effect of officer race and gender on the likelihood of force
- We model this using an IV approach which uses the availability rate of a given officer race/gender as an instrument for the presence of such an officer at a call
- For example, the black officer availability rate is constructed as follows

$$BlackAvailRate_c = \frac{Number\ of\ Available\ Black\ Officers_c}{Number\ of\ Officers\ on\ Shift_c} \tag{1}$$

- Officers are counted as available if they are on shift during the time of the call and not occupied with another call

Models and Results

- First Stage:

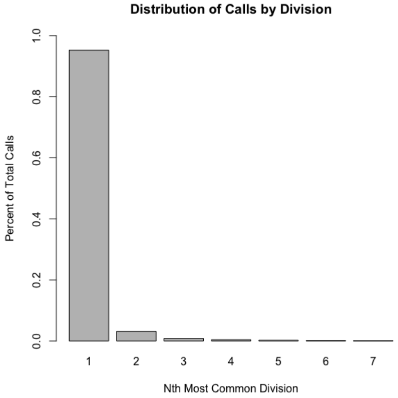
$$BlackOfficer_c = \alpha_0 + \alpha_1 (BlackAvailRate)_c + \theta X_c + FE + \epsilon_c \tag{2}$$

- Second Stage:

$$ForceUsed_c = \beta_0 + \beta_1 (\widehat{BlackOfficer})_c + \delta X_c + FE + \epsilon_c \tag{3}$$

- $BlackOfficer_c$: Equal to 1 when a black officer is present at call c
- $ForceUsed_c$: Equal to 1 when force is used at call c
- X_c: set of call characteristics including call type, priority, and time between call and dispatch
- FE includes $Division * Year * Week * Shift$, day of week, and hour fixed effects

Choice of Fixed Effects



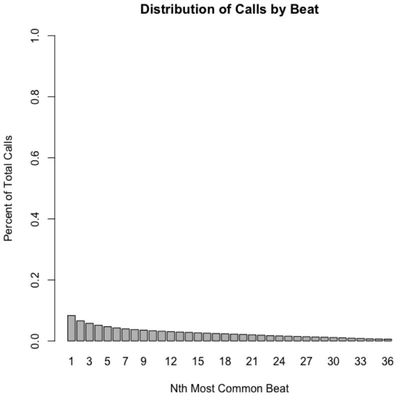


Table: Effect of Officer Race & Gender on Use of Force

	(1)	(2)	(3)	(4)
	OLS	**First Stage**	**Reduced Form**	**IV**
Dependent Variable:	Force Used	B/H/W Officer Present	Force Used	Force Used
Panel A:				
Black Officer Present	0.009***	-	-	-0.018
	(0.002)	-	-	(0.017)
Black Availability Rate	-	0.894***	-0.016	-
	-	(0.13)	(0.017)	-
Mean of Dependent Variable:	0.033	0.474	0.033	0.033
First Stage F Statistic	-	47.01	-	-
Percent of All Arrests	47%	47%	47%	47%
Panel B:				
Hispanic Officer Present	0.015***	-	-	-0.000
	(0.001)	-	-	(0.020)
Hispanic Availability Rate	-	1.366***	0.000	-
	-	(0.117)	(0.03)	-
Mean of Dependent Variable:	0.033	0.47	0.033	0.033
First Stage F Statistic	-	135.40	-	-
Percent of All Arrests	47%	47%	47%	47%
Call Controls	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Division-Year-Week-Shift FE	Yes	Yes	Yes	Yes
Observations	37,682	37,359	37,359	37,359

Table: Effect of Officer Race & Gender on Use of Force

	(1)	(2)	(3)	(4)
	OLS	**First Stage**	**Reduced Form**	**IV**
Dependent Variable:	Force Used	B/H/W Officer Present	Force Used	Force Used
Panel C:				
White Officer Present	0.021***	-	-	0.034
	(0.003)	-	-	(0.022)
White Availability Rate	-	0.647***	0.022	-
	-	(0.071)	(0.016)	-
Mean of Dependent Variable:	0.033	0.777	0.033	0.033
First Stage F Statistic	-	82.06	-	-
Percent of All Arrests	78%	78%	78%	78%
Panel D:				
Female Officer Present	0.008**	-	-	-0.039***
	(0.002)	-	-	(0.014)
Female Availability Rate	-	1.477***	-0.058**	-
	-	(0.094)	(0.023)	-
Mean of Dependent Variable:	0.033	0.421	0.033	0.033
First Stage F Statistic	-	249.44	-	-
Percent of All Arrests	42%	42%	42%	42%
Call Controls	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Division-Year-Week-Shift FE	Yes	Yes	Yes	Yes
Observations	37,682	37,359	37,359	37,359

Table: Effect of Officer Race on Use of Force by Civilian Race

	(1)	(2)	(3)
Force Used Against:	Black Civilian	Hispanic Civilian	White Civilian
Panel A:			
Black Officer Present	-0.014	-0.002	-0.000
	(0.011)	(0.006)	(0.014)
Mean of Dependent Variable:	0.018	0.008	0.007
First Stage F Statistic	47.01	135.40	82.06
Percent of All Arrests	27%	12%	9%
Panel B:			
Hispanic Officer Present	0.001	-0.011*	0.011
	(0.006)	(0.007)	(0.013)
Mean of Dependent Variable:	0.018	0.008	0.007
First Stage F Statistic	47.01	135.40	82.06
Percent of All Arrests	23%	14%	10%
Panel C:			
White Officer Present	0.033***	0.005	-0.003
	(0.010)	(0.010)	(0.016)
Mean of Dependent Variable:	0.018	0.008	0.007
First Stage F Statistic	47.01	135.40	82.06
Percent of All Arrests	38%	22%	19%
Call Controls	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Division-Year-Week-Shift FE	Yes	Yes	Yes
Observations	37,682	37,359	37,359

Replication Results

- In this section, we replicate the results of Hoekstra & Sloan (2020)
- Hoekstra & Sloan estimate the effect of officer race on use of force using data for 911 calls from two undisclosed cities
- The first city is predominantly black and white, while the second city is predominantly Hispanic and white
- They find that
    - In the first city, white officers use force 60 percent more often than black officers on average
    - Dispatching opposite-race officers increases use of force by 30-60%
    - In the second city, white and Hispanic officers use force at similar overall rates, but white officers increase use of force more than Hispanic officers when dispatched to Hispanic neighborhoods
    - Dispatching an opposite-race officer in this second city roughly doubles the likelihood of use of force

Replication Results

- Civilian race is not known for each call, so Hoekstra & Sloan use the race of the census block group from the call location
- We adapt their specification as follows:

$$\begin{aligned} ForceUsed_{ic} = \beta_0 + \beta_1(ProportionBlackCivilians)_c + Officer_i + \\ \beta_2(WhiteOfficer * ProportionBlackCivilians)_{ic} + \\ Division * Year * Week * Shift_c + DayOfWeek_c + HourOfDay_c + X_c + \epsilon_{ic}, \end{aligned} \tag{4}$$

- We estimate this equation using both the full sample and the arrest sample

Replication Results

Table: Replication of Hoekstra & Sloan Results

	All Calls			Arrests		
	(1)	(2)	(3)	(4)	(5)	(6)
	Use of Force	Use of Force	Use of Force	Use of Force	Use of Force	Use of Force
Panel A: Black and White Neighborhoods						
White Officer	0.0036398***	0.0040296***	0.0033725***	0.0348389	0.032267***	0.034825***
	(0.0004256)	(0.000485)	(0.0090941)	()	(0.0094677)	(0.0095866)
Mean of Dependent Variable:	0.0032672	0.0032672	0.0032672	0.0526283	0.0526283	0.0526283
Observations	830,069	830,069	809,058	48,244	48,244	46,364
Panel B: Hispanic and White Neighborhoods						
White Officer	0.0035101***	0.0038477***	0.0020501**	-0.0333014**	-0.039769**	-0.0463022***
	(0.0006915)	(0.0007959)	(0.0007957)	(0.0160475)	(0.0166799)	(0.0170296)
Mean of Dependent Variable:	0.0033171	0.0033171	0.0033171	0.0542537	0.0542537	0.0542537
Observations	1,250,779	1,250,779	1,205,032	72,032	72,032	69,044
Division-Year-Week-Shift FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Officer FE	-	Yes	Yes	-	Yes	Yes
Officer Controls	-	-	Yes	-	-	Yes
Call Controls	-	-	Yes	-	-	Yes

The Effect Of Not Prosecuting Drug Offenses On Overdose Deaths: Evidence From A Natural Experiment

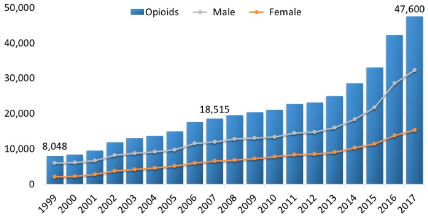
Joint with Maryah Garner - PhD student @ CGU

Background

- Many district attorneys are pledging to stop prosecuting low-level offenses with the intent of reducing mass incarceration
- Several are focusing on non-violent drug offenses:
  - On June 14, 2019, the Santa Clara County District Attorney's Office announced that they will stop prosecuting people for minor drug offenses
  - In May 2019, Dallas County District Attorney, John Creuzot, announced that he wouldn't prosecute many low-level crimes
  - Suffolk County District Attorney, Rachael Rollins' successful 2018 election platform was to not prosecute 15 different types of low-level offenses
  - St Louis County's District Attorney Wesley Bell ran his successful 2018 election promising to stop prosecuting low level offenses that have led to mass incarceration

Background

- There are concerns about the negative ramifications of not prosecuting drug offenses
- The addictive nature of drugs makes non-prosecution of drug offenses potentially concerning
- Critics argue that not prosecuting drug offenses reduces the cost of consuming drugs, which will lead to higher rates of drug use and addiction
- Some politicians also argue that the US is in the middle of an opioid epidemic, so now is not the time to "go easy" on prosecuting drug crimes



Plausible Exogeneity

- Our research aims to examine the effect of not prosecuting drug offenses on overdoes deaths

- Using instances where DA's stopped prosecuting drug offenses will struggle with identification:
  - If a DA is elected on a platform of not prosecuting these offenses, it is because sympathetic voters comprise a large enough share of the electorate
  - It is likely that similar enforcement policies have already been implemented
  - One must consider the environment that would lead a DA to make these decisions
  - Many California counties are currently struggling with jail capacity constraints and are having to release inmates before their sentence is fully served
  - Since these concerns were likely impacting decisions of actors in the criminal justice system, this creates a reverse causality issue for estimation.

- To overcome these issues, we will make use of a unique situation in San Francisco that restricted the DA's ability to prosecute drug offenses

Plausible Exogeneity

- The San Francisco drug lab is charged with testing all suspected drugs seized by law enforcement officers within San Francisco County.
- The responsibilities of the technician include:
  - performing chemical analyses on all suspected drugs
  - Identifying if the alleged narcotic is, in fact, an illegal substance
  - If so, they measure the weight of the narcotic as well as the potency
  - They are responsible for testifying in court in cases that make it to trial
- In 2009 there were only three technicians who worked in the San Francisco drug lab, each handling 5,000 - 7,000 cases per year.
- Deborah Madden was a veteran technician, having worked at the San Francisco drug lab for 29 years.

Plausible Exogeneity

- **September 2009** Madden began acting erratic, missing work, working overtime (alone) and not requesting compensation. She was confronted by her superior for going through co-workers evidence lockers without permission.
- **November 2009** Deputy DA Woo wrote an email to the chief deputy of the DA's office stating "Madden appeared to be purposely sabotaging cases by calling in sick on days she was to testify in court"
- **December 2009** Madden checked herself into an alcohol rehabilitation facility
- **December 2009** Madden's sister found cocaine in what appeared to be a lab evidence vial, and reported her findings to Madden's boss, Lois Woodworth

Plausible Exogeneity

- **December 2009** Woodworth opened an internal audit into evidence processed by Madden.
- The audit reviewed 25 randomly selected evidence samples of cocaine that Madden had processed.
  - **7** of the **25** were found to have a shortage of cocaine
- **February 16, 2010** Woodworth's finding were turned over to police
- **March 1, 2010** Madden retired from the drug lab
- **March 3, 2010** Madden was arrested
- **March 9, 2010** The drug lab was shut down and all future cases that the DA felt were worth pursuing had to be tested in Alameda County.
  - Greatly increased the cost for the SF DA's office to prosecute drug cases
  - Substantially reducing the amount of drug cases pursued by the DA's office

Research Question

- How did the drug lab shut down affect the DA's ability to prosecute drug-related offenses?
- How did the shift in DA's charging behavior impact the arresting decisions of law enforcement officers?
- Does not prosecuting/arresting drug offenses have an effect on public health (overdose deaths)?

Data

- Criminal Offender Record Information (CORI) data from California Department of Justice
- Drug Overdose Deaths: Cause of Death data files constructed by the Centers for Disease Control and Prevention (CDC)
- Drug Abuse Warning Network (DAWN)
- Demographics: American Community Survey (ACS)

Summary Stats

Monthly Averages Per 100K Persons	Before	After	Difference	P-Value
San Francisco				
Dismissals - Drug Cases	47.53	26.08	-21.45	0.00
Drug Arrests	142.92	75.17	**-67.76**	0.00
Dismissals - Theft Cases	54.26	44.67	-9.59	0.14
Theft Arrests	53.23	44.77	-8.47	0.14
Dismissals - Burglary Cases	4.92	3.92	-0.99	0.008
Burglary Arrests	22.59	22.83	0.24	0.76
Overdose Death	1.83	1.80	**-0.09**	0.42
All Other Counties				
Dismissals - Drug Cases	7.32	10.23	2.92	0.00
Drug Arrests	95.93	92.81	**-3.12**	0.06
Dismissals - Theft Cases	2.96	3.40	0.45	0.0
Theft Arrests	42.89	39.66	-3.23	0.00
Dismissals - Burglary Cases	1.27	1.43	0.17	0.41
Burglary Arrests	17.89	17.74	-0.15	0.58
Overdose Death	1.16	1.36	**0.21**	0.00

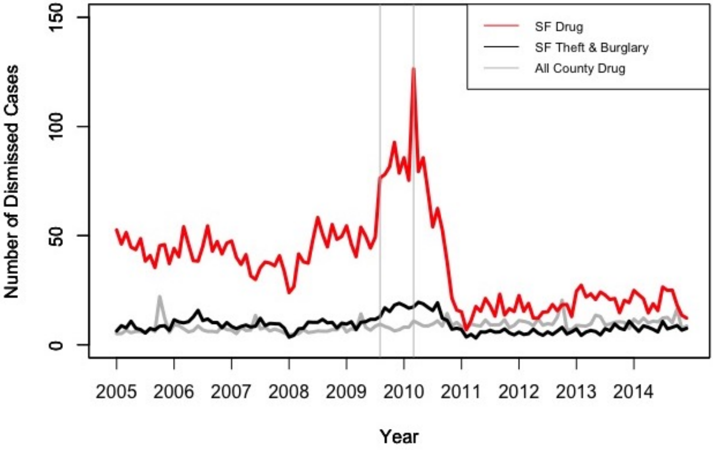


Figure: Cases Dismissed by Prosecutors per 100,000 persons

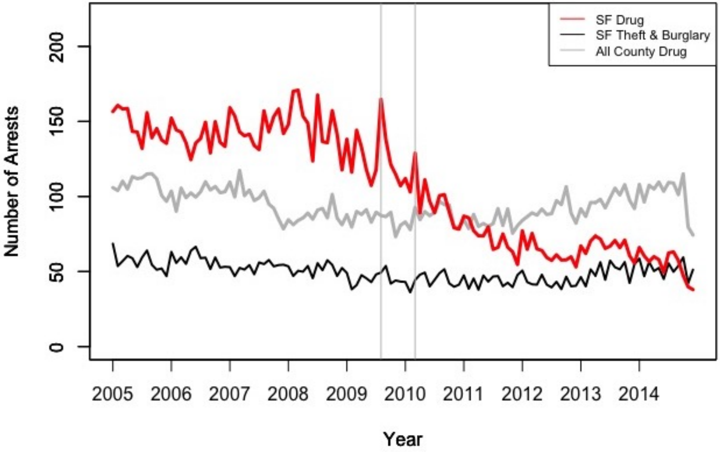


Figure: Arrests per 100,000 Persons

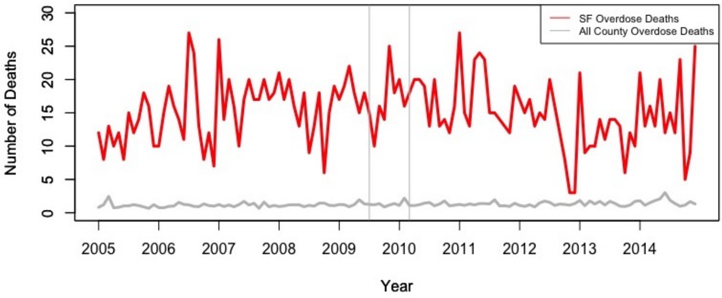


Figure: Overdose Deaths per 100,000 Persons

Dynamic Difference-in-Difference for Drug Arrests

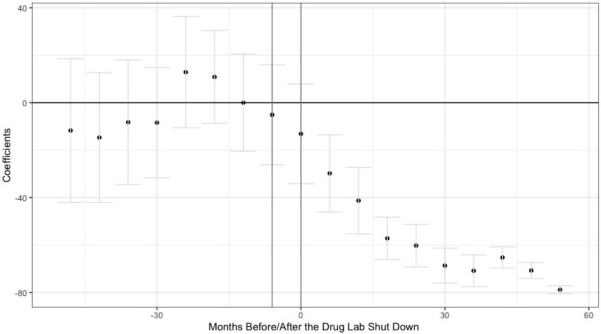


Figure: Dynamic DD Graph for for Drug Arrests

Dynamic Difference-in-Difference for Overdose Deaths

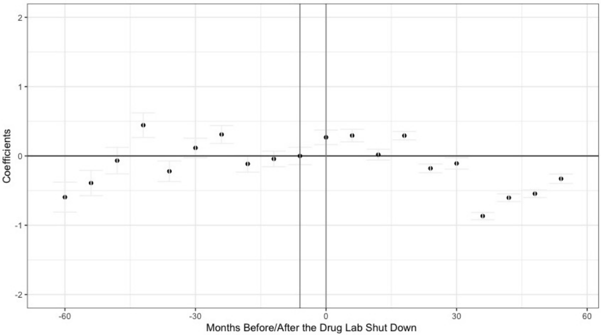


Figure: Dynamic DD Graph for Overdose deaths

Difference-in-Difference Model

$$y_{it} = \beta_1 Treat_{it} + \boldsymbol{\tau_t} + \boldsymbol{\alpha_i} + \boldsymbol{X_t} + \epsilon_{it}, \tag{5}$$

- $\boldsymbol{\alpha_i}$ are county fixed effects that capture all time-invariant county-level variation
- $\boldsymbol{\tau_t}$ are year-by-month fixed effect that captures all time-varying unobserved variation that is constant across counties
- $\boldsymbol{X}$ is a vector of county-level demographics that change over time. They include the proportion of the population that is:
    - Black
    - White Hispanic
    - Unemployed
    - College educated

Results

Table: Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shutdown on Arrests for Drug Crimes

	Drug Arrests per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treatment Effect	-66.210^{***}	-66.210^{***}	-63.953^{***}	-56.378^{***}
	(3.376)	(3.401)	(6.245)	(9.608)
Mean of Pre-treatment Arrests for SF	140	140	140	140
County FEs	X	X	X	X
Month and Year FEs	X			
Month-by-year FEs		X	X	X
County Demographic controls			X	X
Weighted by county population				X
Observations	6,608	6,608	3,894	3,894
R^2	0.714	0.720	0.863	0.910

Results

Table: Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shutdown on Drug Overdose Deaths

	Drug Overdose Deaths per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treatment Effect	-0.373^{***}	-0.373^{***}	-0.338^{***}	-0.239^{***}
	(0.049)	(0.049)	(0.127)	(0.078)
Mean of Overdose Deaths for SF	1.869	1.869	1.869	1.869
County FEs	X	X	X	X
Month and Year FEs	X			
Month-by-year FEs		X	X	X
County Demographic controls			X	X
Observations	6,608	6,608	3,894	3,894
R^2	0.116	0.129	0.492	0.713

Robustness Checks

- Within San Francisco County difference-in-difference
- Restricted time frame (newly appointed DA)
- Statistical Inference from the Placebo Treatment Distribution

Robustness Checks

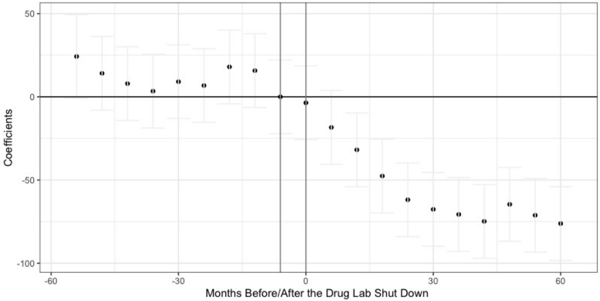


Figure: Dynamic DD Graph for Drug Arrests: Drug Arrests vs. Theft + Burglary.

Robustness Checks

Table: Within-County Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shut Down on Arrests for Drug Crimes

	Arrests per 100,000 Residents			
	(1)	(2)	(3)	(4)
Post*Drug	-61.261^{***}	-61.261^{***}	-61.261^{***}	-61.261^{***}
	(3.394)	(2.956)	(2.742)	(3.150)
Post	-7.844^{***}	23.240^{***}	31.756^{***}	
	(2.400)	(5.283)	(6.200)	
Drug	64.818^{***}	64.818^{***}	64.818^{***}	64.818^{***}
	(2.327)	(2.026)	(1.880)	(2.160)
Mean of Pre-treatment Arrests for SF	140	140	140	140
County Demographic controls		X		
Month and Year FEs			X	
Month-by-year FEs				X
Observations	234	234	234	234
R^2	0.849	0.887	0.910	0.935
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Robustness Checks

Restricted time frame

- On January 9, 2011, George Gascón was appointed as San Francisco District Attorney to succeed Kamala Harris, who had been elected California Attorney General in November 2010
- A potential concern is that our results are driven by the change in district attorney and not the shutting down of the drug lab.

Robustness Checks

Restricted time frame

Table: Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shut Down on Arrests for Drug Crimes

	Drug Arrests per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treatment Effect	-36.600^{***}	-36.600^{***}	-34.239^{***}	-28.478^{***}
	(2.871)	(2.890)	(5.212)	(4.670)
Mean of Drug Arrests for SF	106	106	106	106
County FEs	X	X	X	X
Month and Year FEs	X			
Month-by-year FEs		X	X	X
County Demographic controls			X	X
Weighted by county population				X
Observations	4,176	4,176	2,448	2,448
R^2	0.781	0.789	0.897	0.938

Robustness Checks

Restricted time frame

Table: Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shut Down on Drug Overdose Deaths.

	Drug Overdose Deaths per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treat	−0.003	−0.003	0.014	0.065
	(0.094)	(0.095)	(0.217)	(0.047)
Mean of OD Deaths for SF	1.869	1.869	1.869	1.869
County FEs	X	X	X	X
Month and Year FEs	X			
Month-by-year FEs		X	X	X
County Demographic controls			X	X
Weighted by county population				X
Observations	4,176	4,176	2,448	2,448
R^2	0.078	0.090	0.494	0.716

Drug Arrests

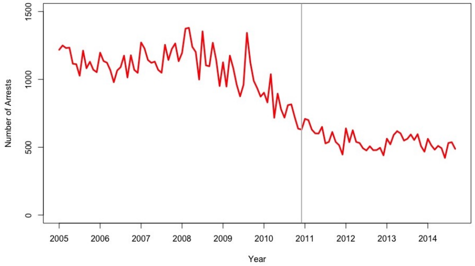


Figure: Drug Arrests in San Francisco County with DA Change

- The drug lab shutting down had a compounding effect on arrests
- Since we are cutting the sample in the middle of the declining drug arrests, we would expect the estimated effect to be substantially smaller
- There was no discontinuity in the monthly reduction of drug arrests when George Gascón was appointed DA
- If the estimated effect was driven by the change in DA and not the drug lab shutdown, we would expect drug arrests to remain steady until George Gascón became the DA and then exhibit a kink

Statistical Inference from the Placebo Treatment Distribution

- Due to serial correlation in standard errors that are prominent in most difference-in-difference estimations, there is concern that the clustered standard errors are too small and could lead to improper statistical inference.
- Follow the lead of Bertrand et al. (2004) and use the empirical distribution of estimated effects for placebo treatments to form the test distribution.

Statistical Inference from the Placebo Treatment Distribution

Procedure:

- Assign first county in sample as the treated unit starting in January 2007 and then use the other 57 counties as control units, then estimate the treatment effect.
- Then assign that same county as the treated unit starting in February 2007 and again estimate the treatment effect.
- Continue this process for first county until October 2012.
- Repeat the process for each of the remaining 56 counties (excluding San Francisco County).
- This leads to 118 placebo treatment times for each of the 57 California counties, total of 6,726 estimated placebo treatment effects.

Statistical Inference from the Placebo Treatment Distribution

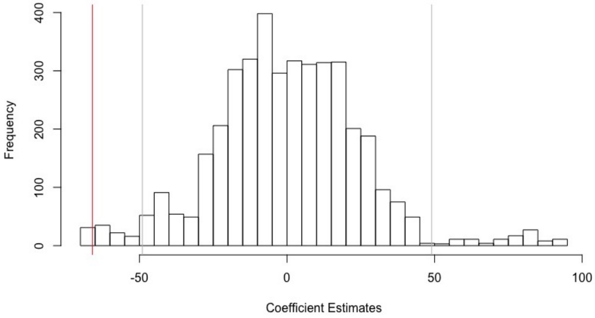


Figure: Placebo Treatment Distribution for Drug Arrests

Statistical Inference from the Placebo Treatment Distribution

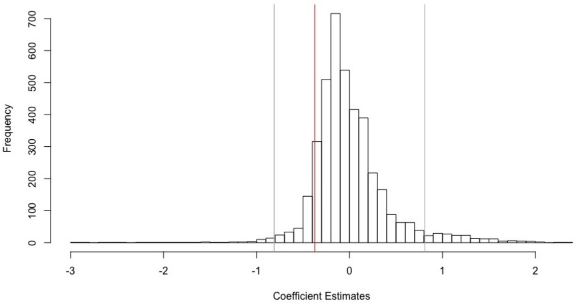


Figure: Placebo Treatment Distribution for Overdose Deaths

Racial analysis

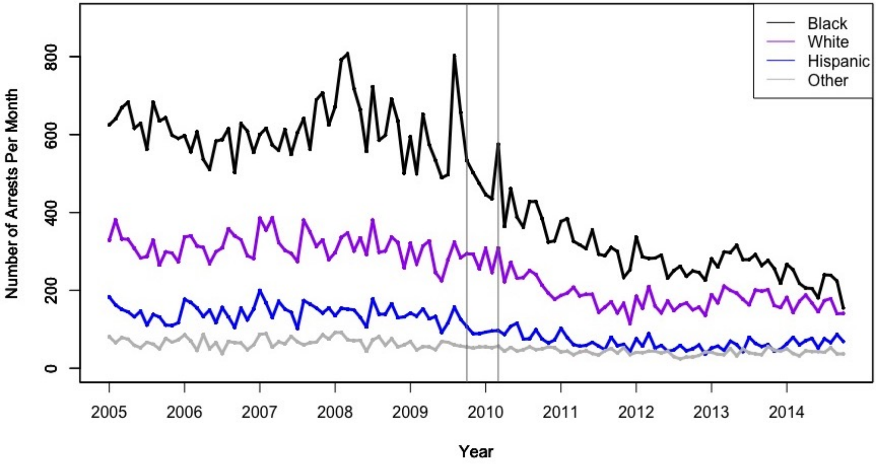


Figure: Drug Arrests by Race in San Francisco

Racial analysis

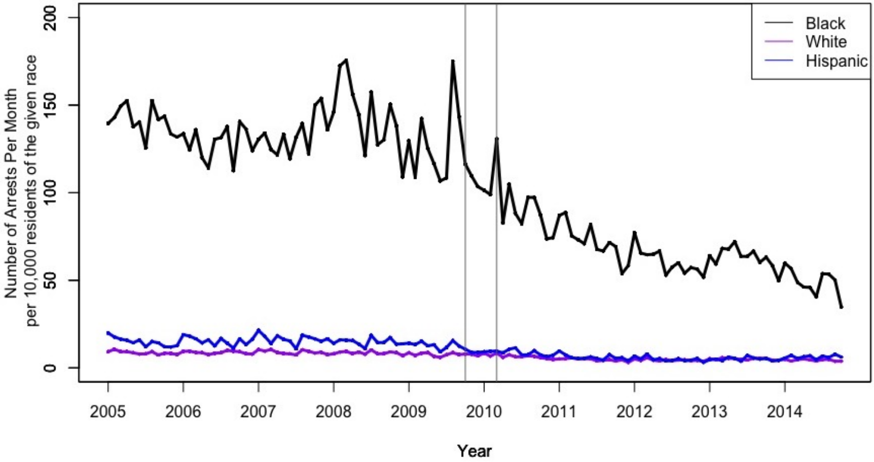


Figure: Drug Arrests per 100,000 by Race in San Francisco

Racial analysis

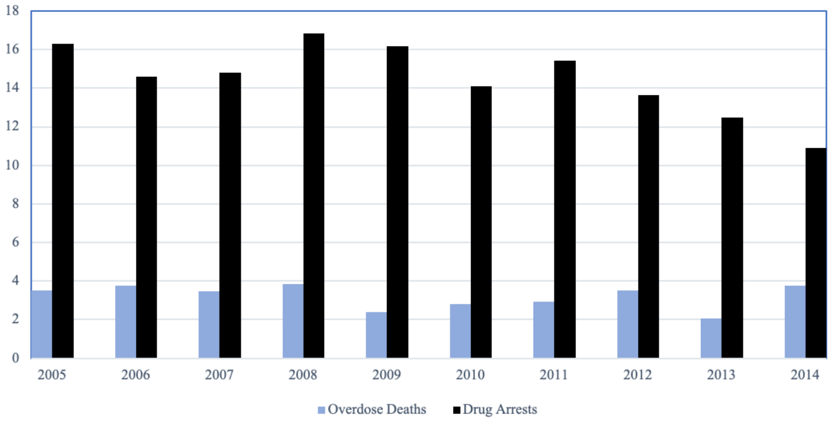


Figure: Overdose Deaths and Drug Arrests for Blacks Relative to Whites

Racial analysis

Table: Difference-in-Difference Estimates of the Effect of San Francisco County Drug Lab Shutdown on Drug Arrests for Black Citizens

	Drug Arrests per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treatment Effect	$-1{,}980.361^{***}$	$-1{,}980.361^{***}$	$-1{,}945.394^{***}$	$-1{,}954.099^{***}$
	(9.941)	(10.001)	(36.500)	(30.245)
Mean of Dependent Variable for SF	1.869	1.869	1.869	1.869
County FEs	X	X	X	X
Quarter and Year FEs	X			
Quarter-by-year FEs		X	X	X
County Demographic controls			X	X
Weighted by county population				X
Observations	2,184	2,184	1,287	1,287
R^2	0.964	0.965	0.977	0.942

- We estimate that the drug lab shutdown caused a reduction of 660.12 monthly drug arrests per 100,000 Black residents.
- This is a reduction in monthly arrest rates that is 10-times larger than the estimated effect for the total population

Table: Difference-in-Difference Estimates of the effect of San Francisco County Drug Lab Shutdown on Overdose Deaths for Black Citizens

	Drug Overdose Deaths per 100,000 residents			
	(1)	**(2)**	**(3)**	**(4)**
Treat	-4.504^{***}	-4.504^{***}	-4.402^{***}	-4.093^{***}
	(0.139)	(0.140)	(0.249)	(0.203)
Mean of Pre-treatment Overdose for SF	25.28	25.28	25.28	25.28
County FEs	X	X	X	X
Quarter and Year FEs	X			
Quarter-by-year FEs		X	X	X
County Demographic controls			X	X
Weighted by county population				X
Observations	2,184	2,184	1,287	1,287
R^2	0.488	0.492	0.831	0.863

Emergency Department visits

- While looking at overdose deaths is important, there is still a concern that not prosecuting and arresting drug offenses will lead to excess (ab)use of drugs, to the point of requiring medical care.

Emergency Department visits

- While looking at overdose deaths is important, there is still a concern that not prosecuting and arresting drug offenses will lead to excess (ab)use of drugs, to the point of requiring medical care.

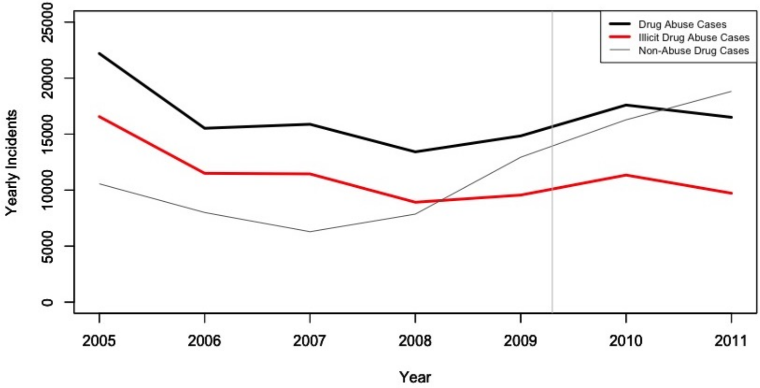


Figure: Emergency Departments Visits for Drug-Related Events

Future CJL Projects

- Pretrial detention and recidivism
- Dispatcher priming and officer use of force
- Implicit bias in criminal cases
- Impact of training on biases in the criminal justice system