Policing in Chicago

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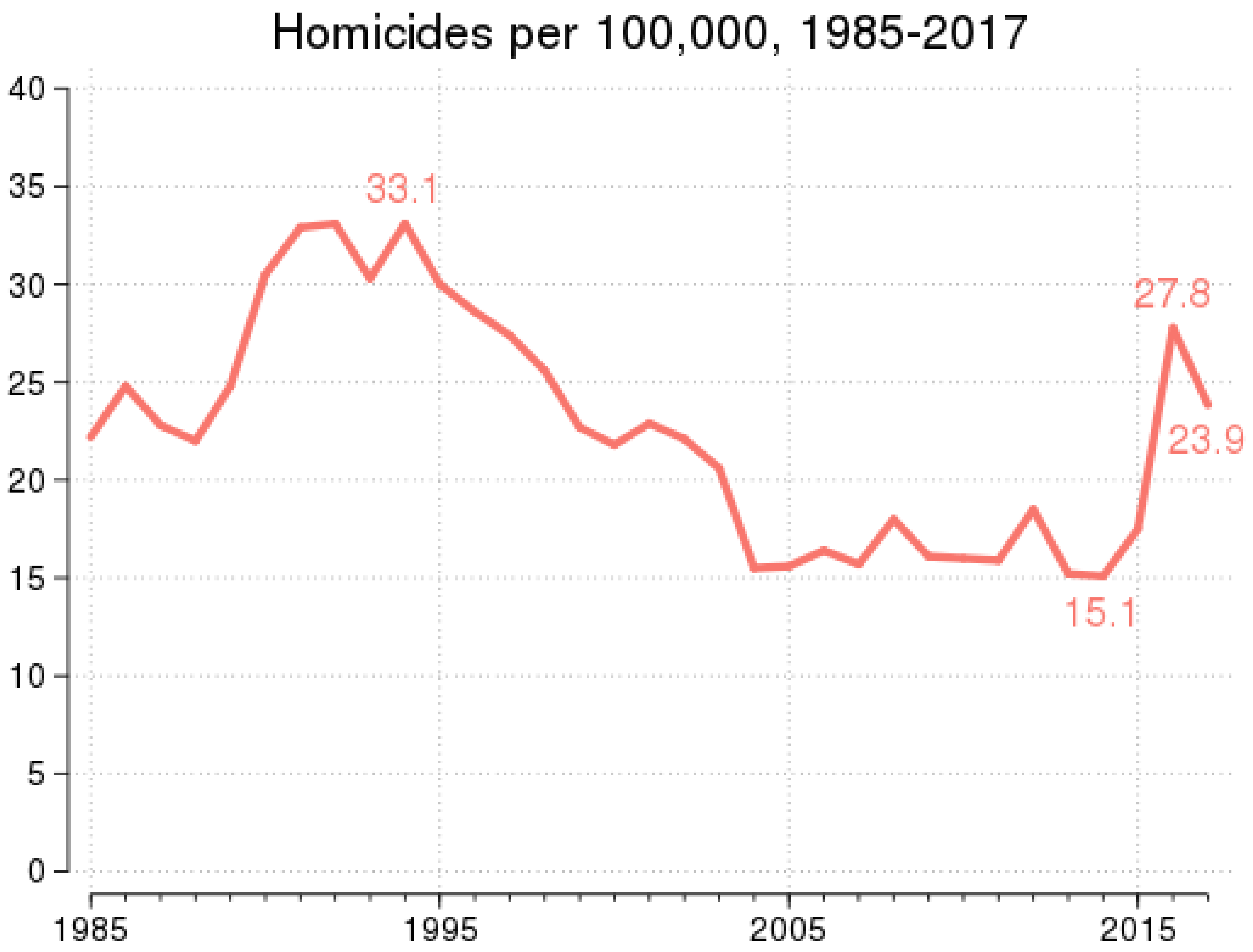
Homicides per 100,000, 1985-2017
40
35
30
25
20
15
10
5
0
33.1
27.8
23.9
15.1
1985
1995
2005
2015

CPD’s response to 2016

- Strategic Decision Support Centers (SDSCs), collaboration between:
    - Chicago Police Department (CPD)
    - Mayor’s Office
    - Chief Sean Malinowski (LAPD)
    - University of Chicago Crime Lab

CPD’s response to 2016

- Strategic Decision Support Centers (SDSCs), collaboration between:
    - Chicago Police Department (CPD)
    - Mayor’s Office
    - Chief Sean Malinowski (LAPD)
    - University of Chicago Crime Lab
- What do the SDSCs do?
    - Consider what most experts think are policing best practices

Policing best practices

High-Risk Places

High-Risk Persons

Community Engagement

CPD’s implementation of policing best practices

	Status quo	SDSC
High-Risk Places	• Custom mapping software • Static deployment plans	
High-Risk Persons	• Limited checks of probationers, parolees; open warrants	
Community Engagement	• Chicago Alternative Policing Strategy (CAPS)	

CPD’s implementation of policing best practices

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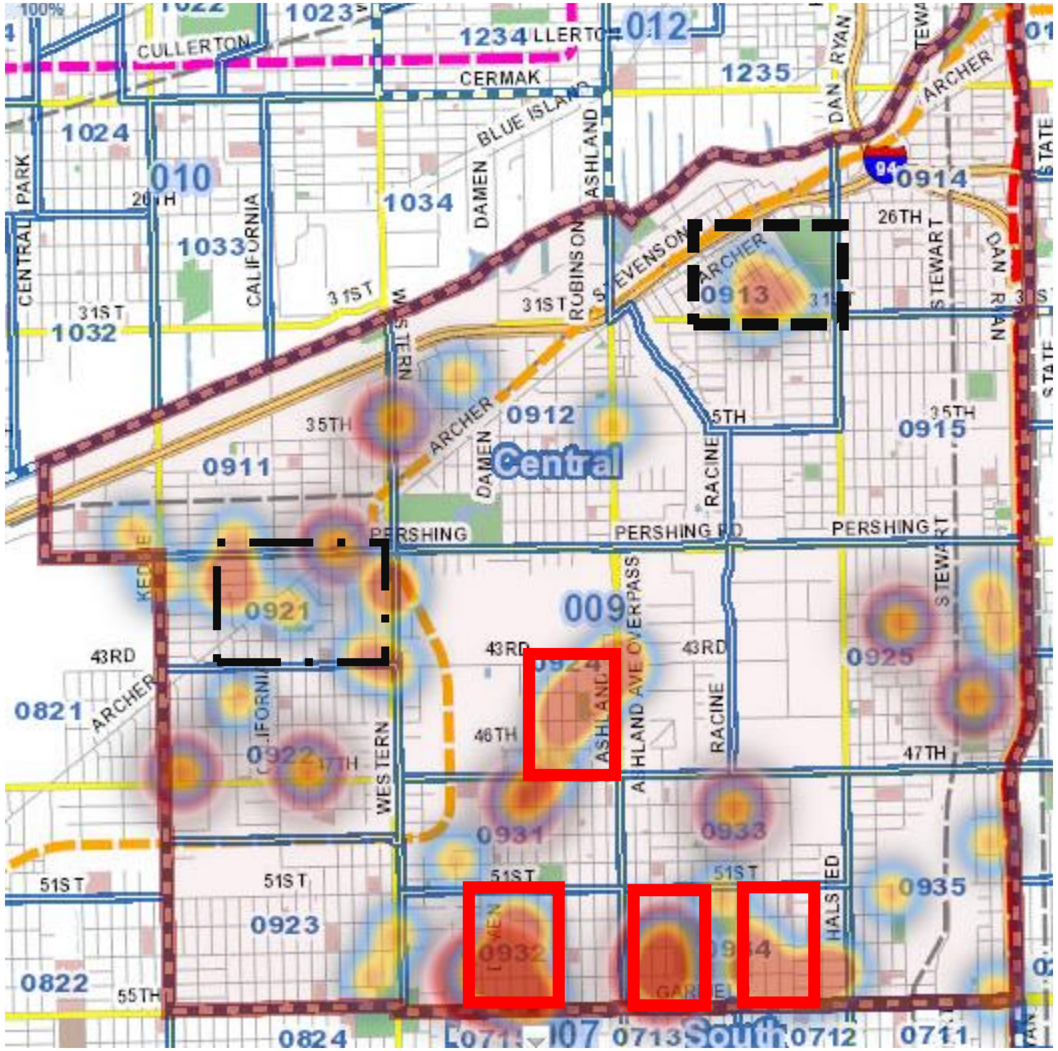
SDSC: Recommendations



Legend:

Foot Patrol

- Archer-31 / River-Halsted

Bike Patrol

- Pershing-Pope/Western-Sac

High Vis Patrol

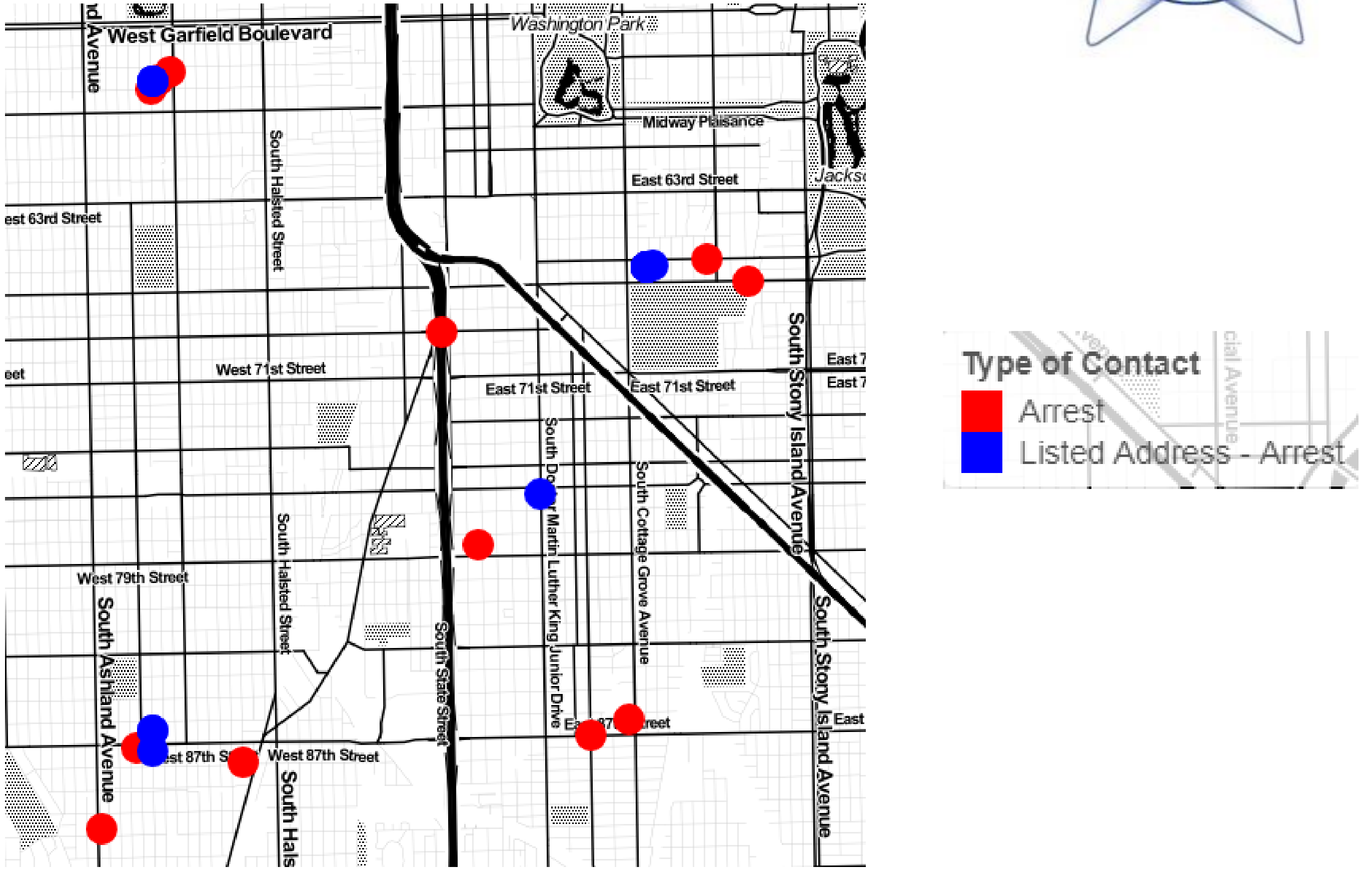
- 43-47 / Wolcott-Ashland
- 51-55 / Hoyne-Winchester
- 51-55 / Ashland-Loomis
- 51-55 / Racine-Carpenter

CPD’s implementation of policing best practices

	Status quo	SDSC
High-Risk Places	• Custom mapping software • Static deployment plans	• Centralized crime mapping (analyst) • Dynamic deployment plans
High-Risk Persons	• Limited checks of probationers, parolees; open warrants	• Identifying high-risk persons in briefings • Information packets for warrant arrests, curfew checks
Community Engagement	• Chicago Alternative Policing Strategy (CAPS)	

ACTIVE WARRANT – CW0046401

JOHN P DOE
IR#
LKA:
SEX/RACE/AGE: M/1/28
HT/WT: 5’04”/180
Issued: 26 June 17



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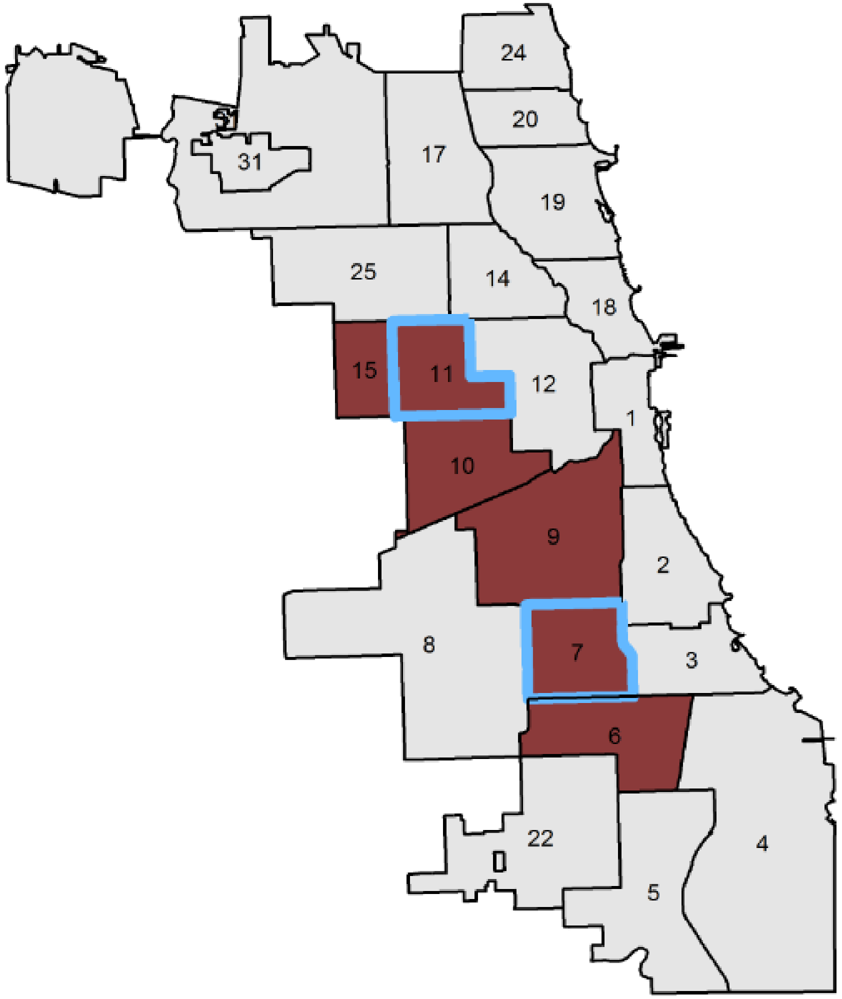
CPD’s implementation of policing best practices

	Status quo	SDSC
High-Risk Places	• Custom mapping software • Static deployment plans	• Centralized crime mapping (analyst) • Dynamic deployment plans
High-Risk Persons	• Limited checks of probationers, parolees; open warrants	• Identifying high-risk persons in briefings • Information packets for warrant arrests, curfew checks
Community Engagement	• Chicago Alternative Policing Strategy (CAPS)	• Measuring positive community interactions

An evaluation challenge

- Feb 2017: Dist. 7 and 11 (23% of homicides)



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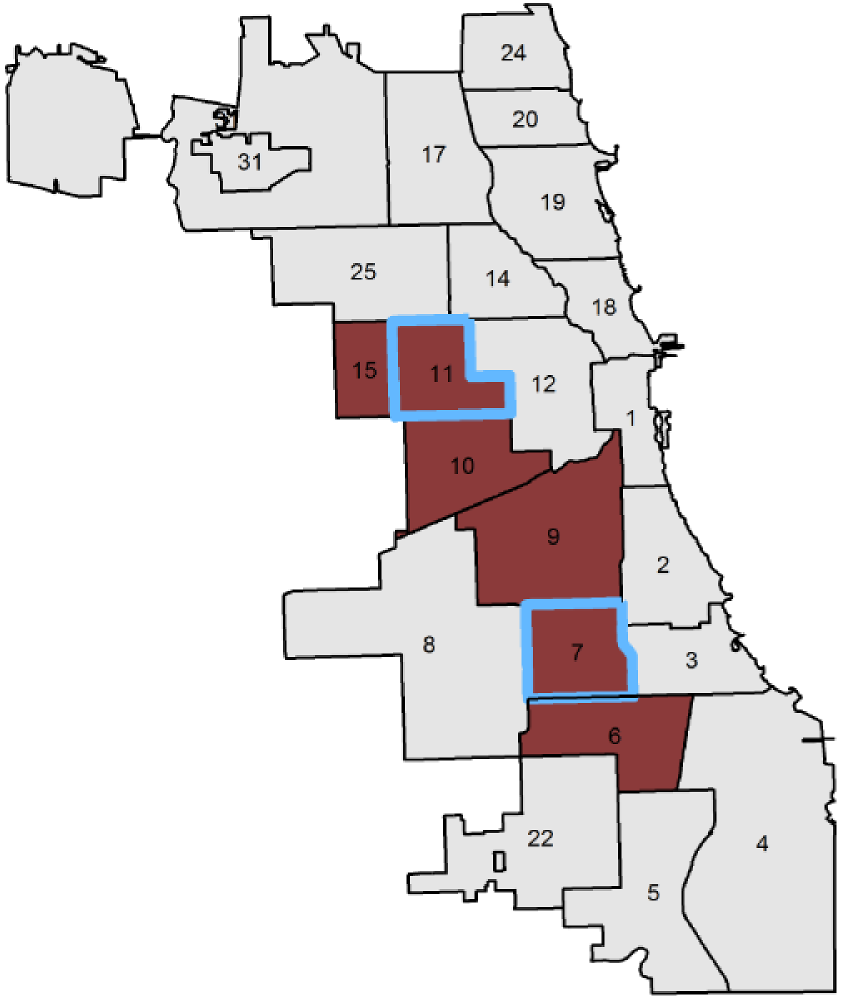

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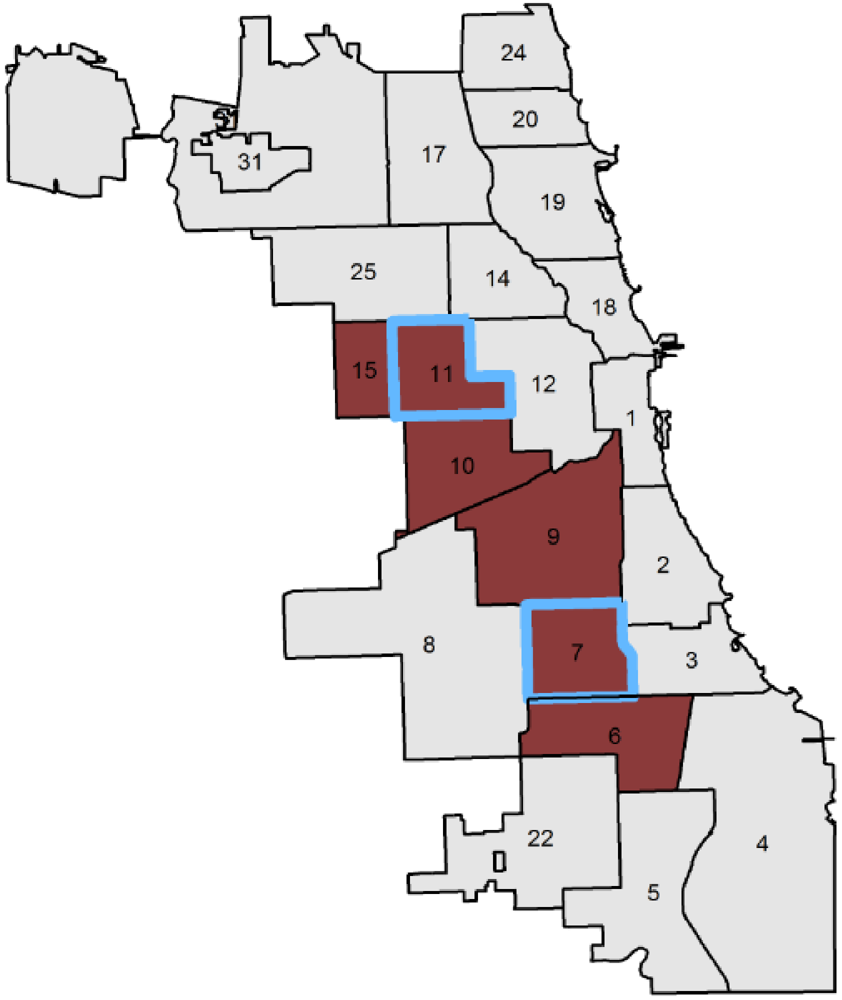

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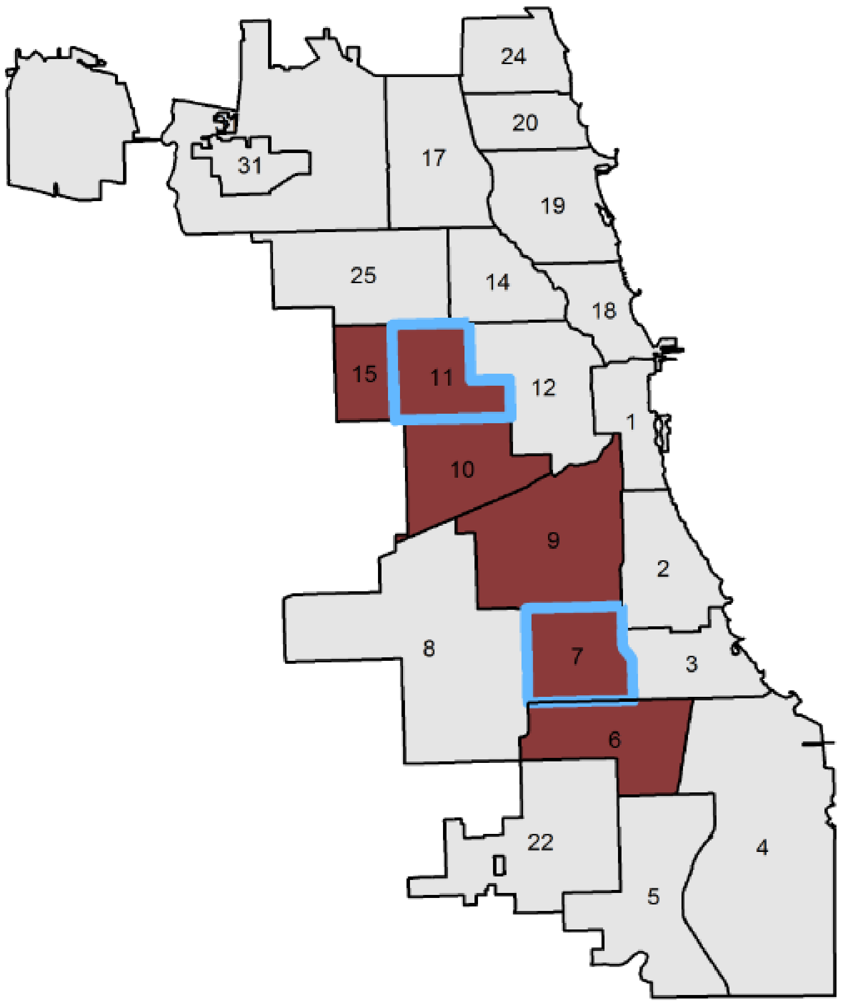

An evaluation challenge

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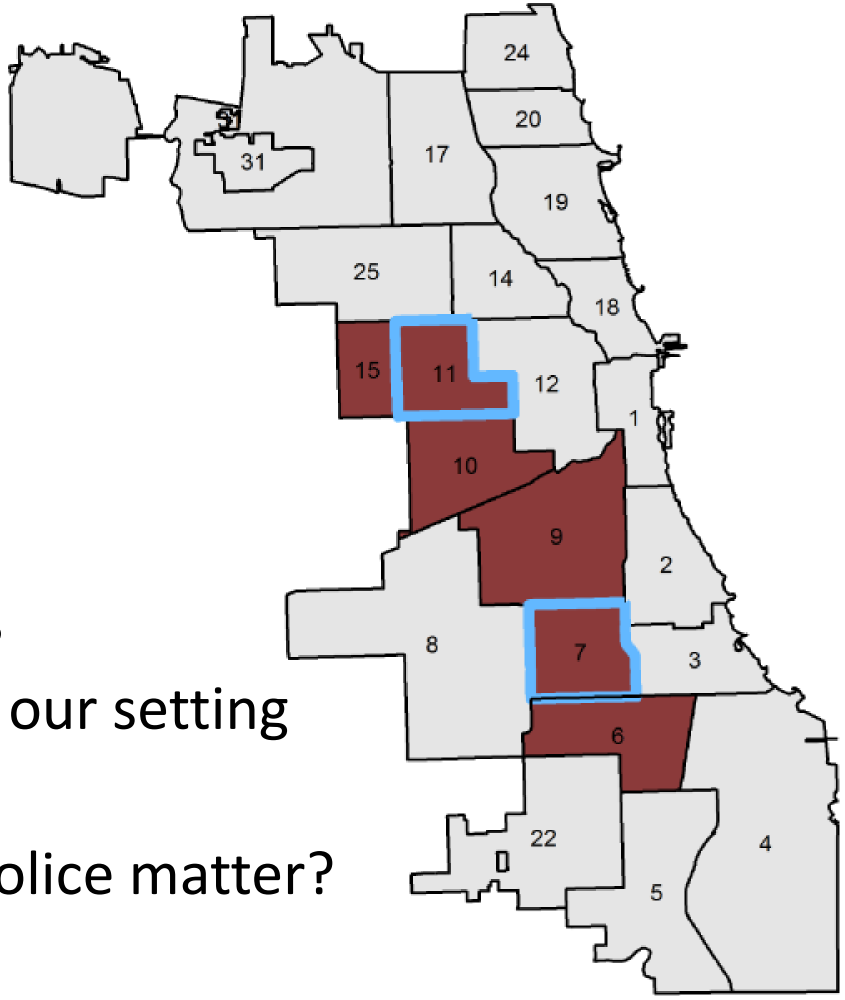
- Synthetic controls for place-based interventions
  - Powerful tool, but saw signs of misleading results in our setting
  - We propose a modified version
  - Variable results across districts sheds light on why police matter?



Intuition

- **Method:** Choose weights (ω_j^*) that minimize the distance between the treated and donor units in the pre-period ($t \leq T$):

$$\underset{\omega}{\arg\min} \sum_{t=1}^{T} \left(Y_{1t} - \sum_{j=2}^{J} \omega_j Y_{jt} \right)^2$$

- **Key assumption:** The relationship between $f(x)$ and the donor units, represented by the weights, remains stable over time.

Avoiding pitfalls

- To reduce over-fitting, make it harder to assign weight to noise donors
  - How do we do this if we don't know which ones are the noise donors?
  - By making it harder to assign weight to *any* donor
  - Data will prioritize (signal) donors that track treated unit more closely, de-prioritize (noise) donors that do not

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  - Rigid constraints: $\omega \geq 0, \ \sum \omega = 1$

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- Doudchenko & Imbens (DI 2017): data-driven penalty on control "complexity"
  - Regularized regression: fewer weights, smaller weights

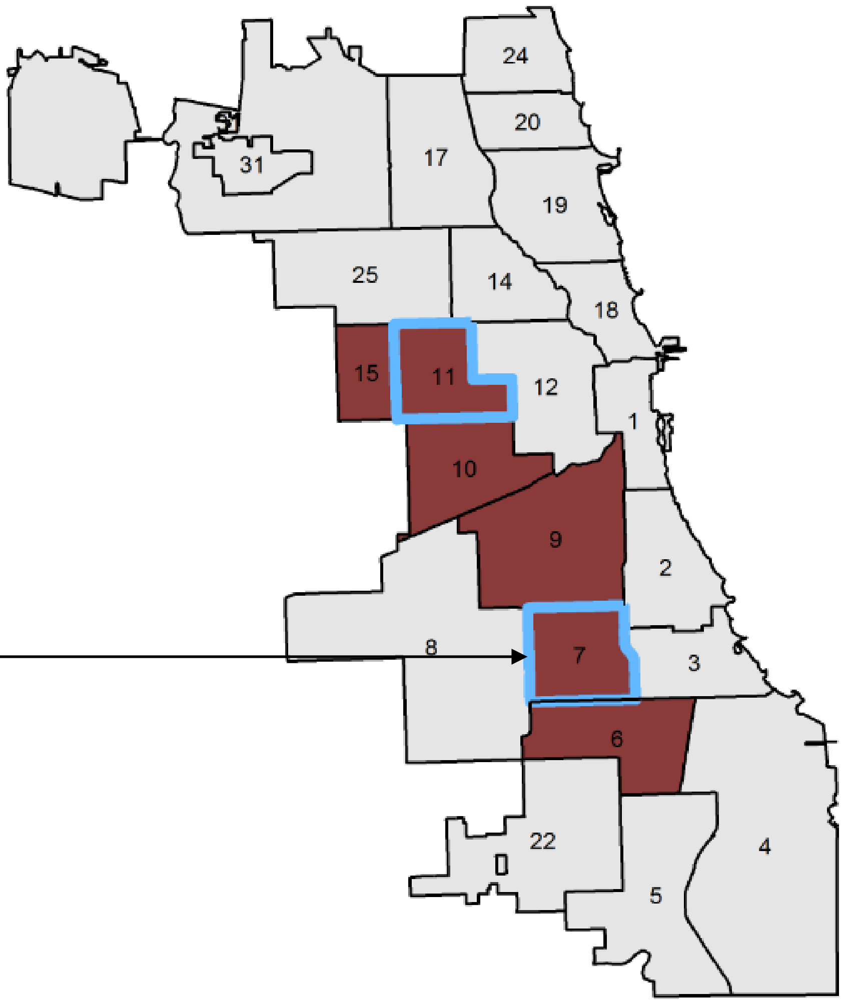
Synthetic Controls:
SDSC Application

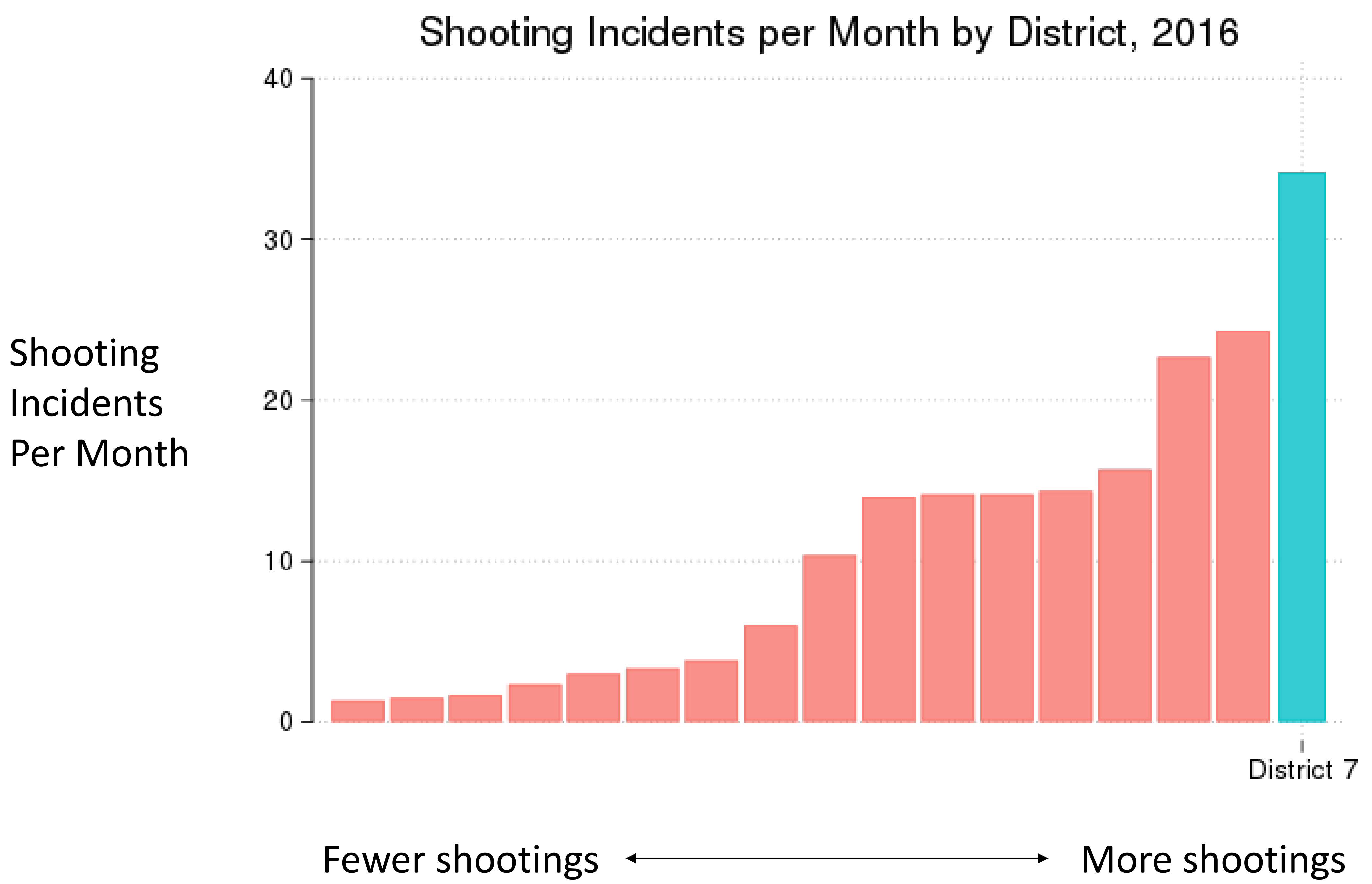
Shootings in District 7

- Focus on District 7
- Weights: ADH (2010, 2015)
  - $\omega \geq 0,\ \sum \omega = 1$

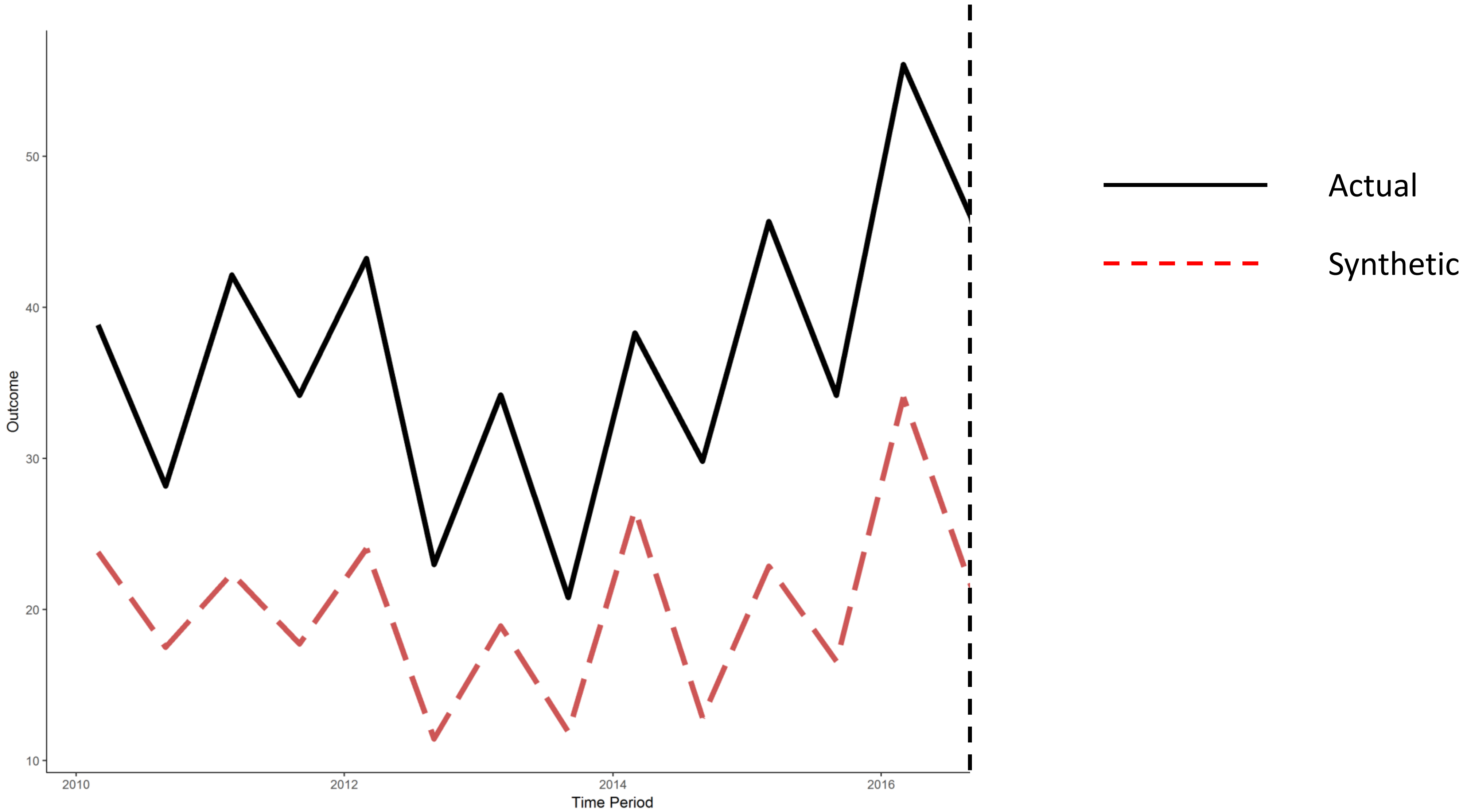
$$\underset{\omega}{\arg\min} \sum_{t=1}^{T_0} \left(Y_{1,t} - \sum_{j=2}^{J+1} \omega_j Y_{j,t} \right)^2$$

- Donors: 16 non-SDSC districts



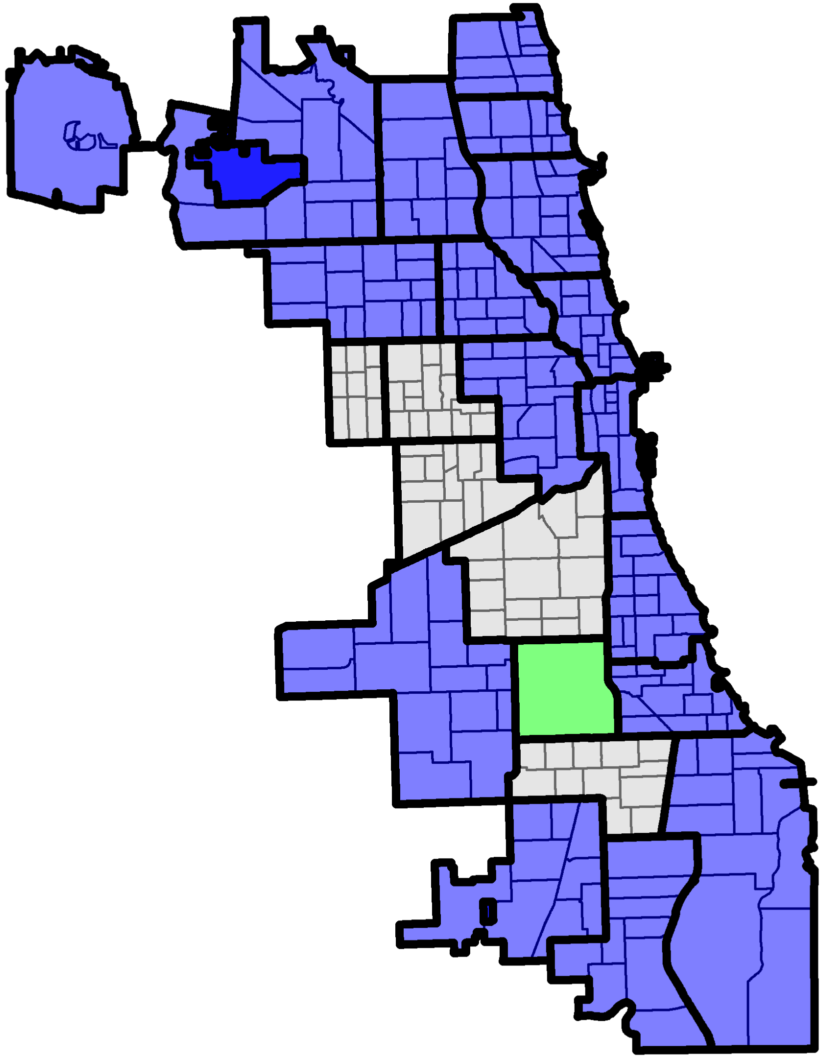

Shooting Incidents per Month by District, 2016
Shooting
Incidents
Per Month
40
30
20
10
0
District 7
Fewer shootings
More shootings

Shooting incidents per month in District 7

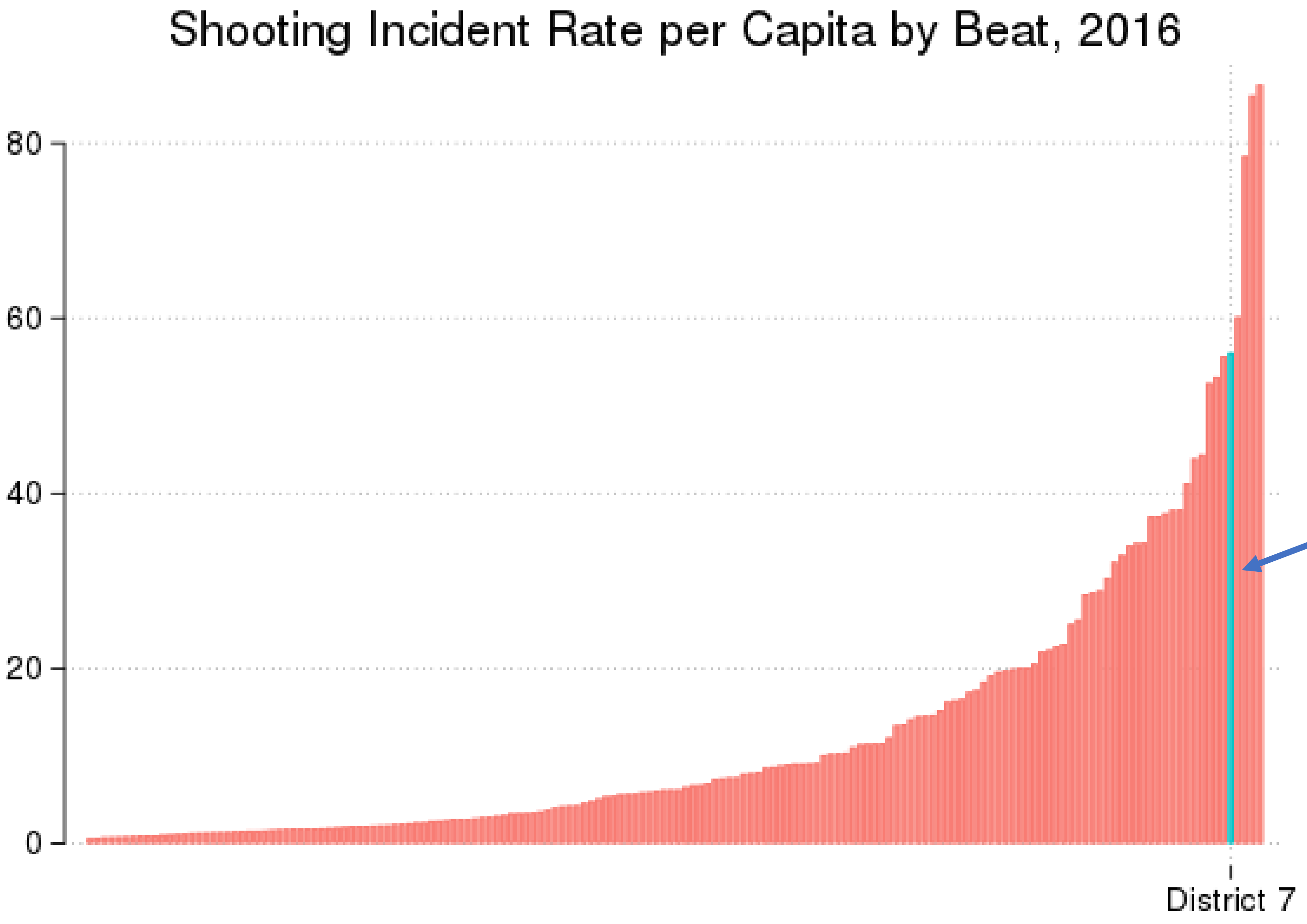


Expanding the donor pool

- Crime data can be aggregated to any geographic unit, not just districts
- What if we use beats within the 16 districts as our donor pool?
  - The 16 districts may look different…
  - …but some of their beats do not.
- To account for difference in size between treated district and donor beats, express outcome as rate per capita



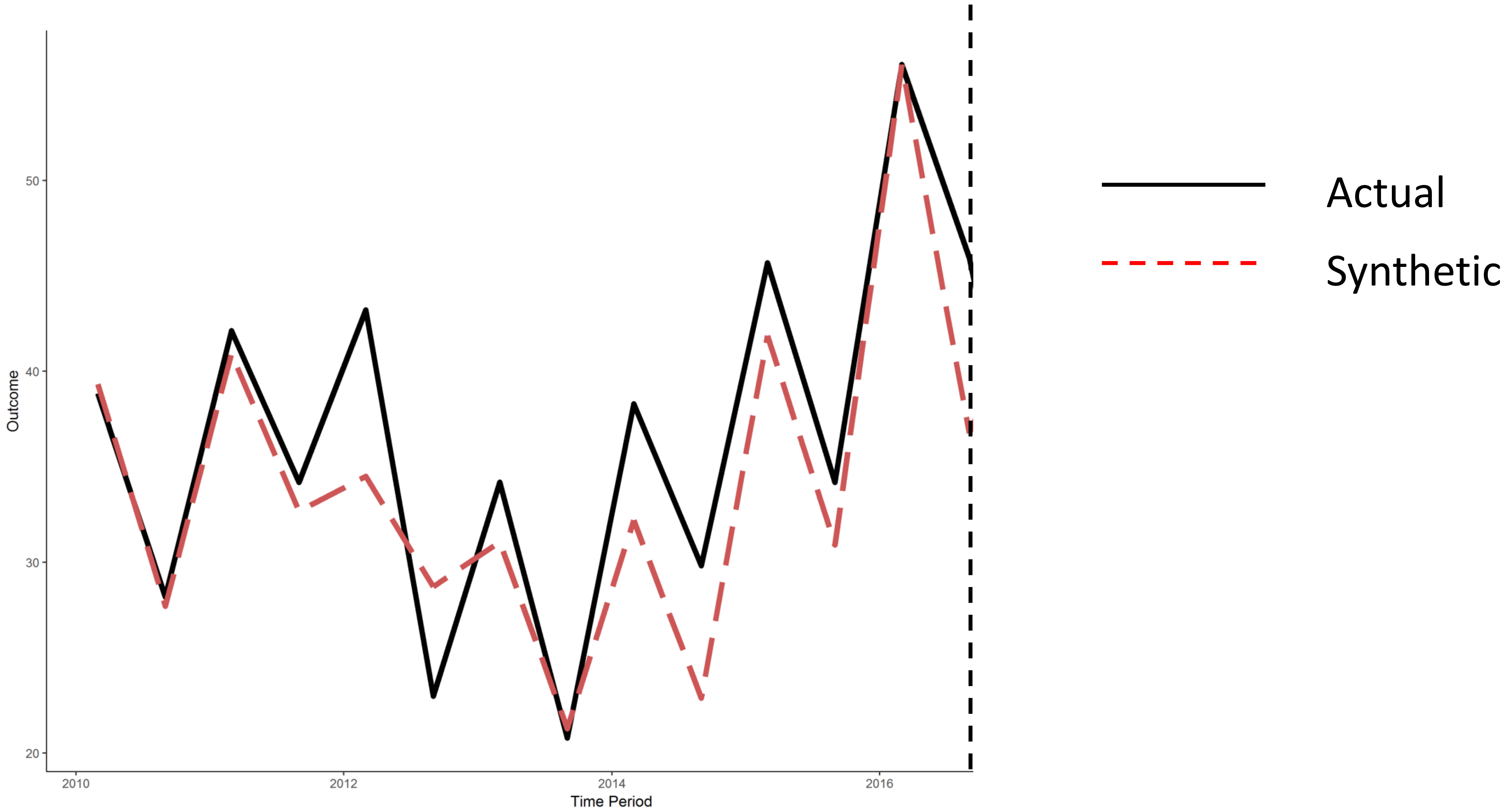
Shooting Incidents Per 100K



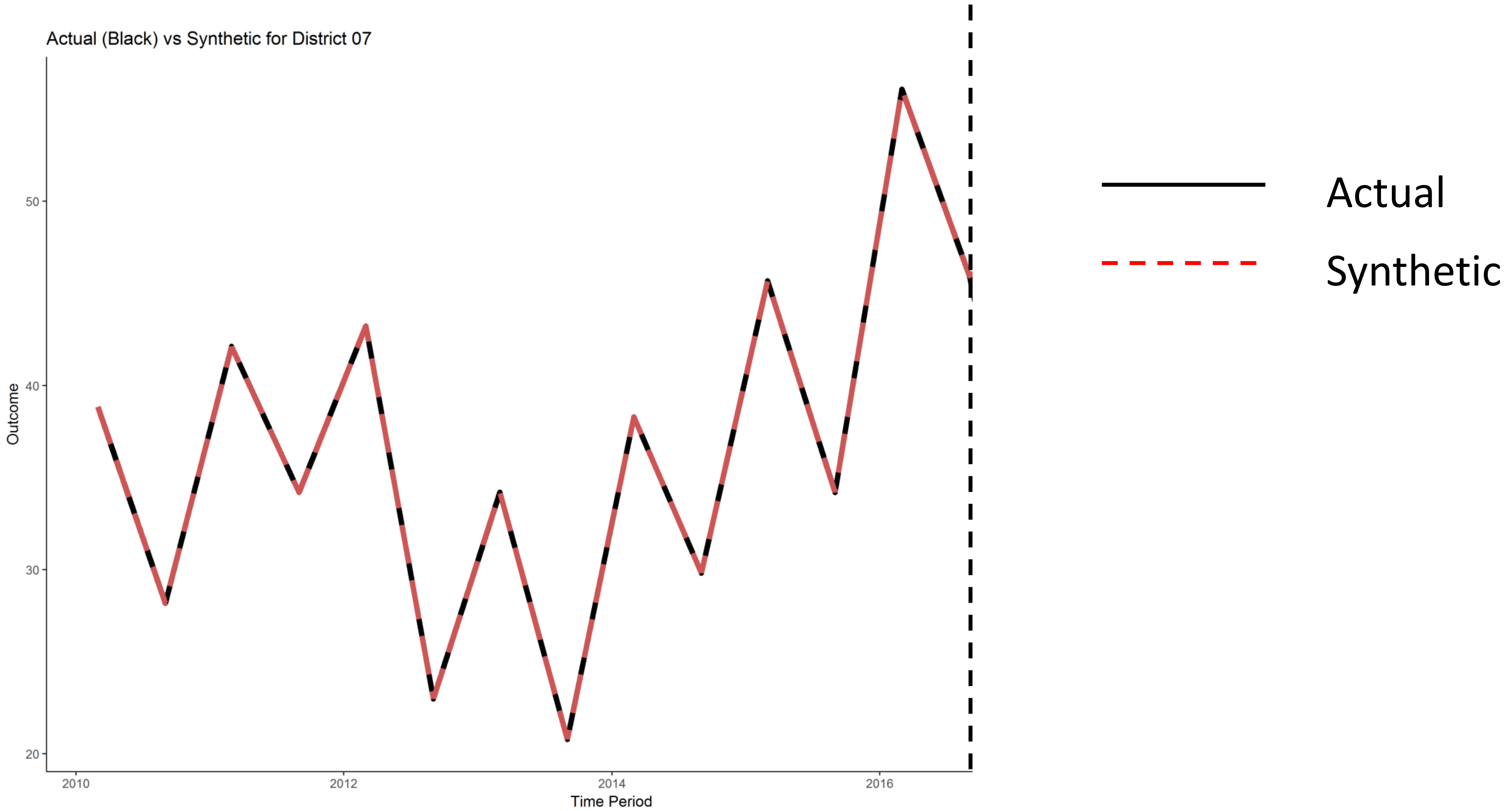
District 7 not total outlier within the beat-level shootings distribution

Fewer shootings ⟷ More shootings

Better, but not great, fit



DI regularized regression: really good fit



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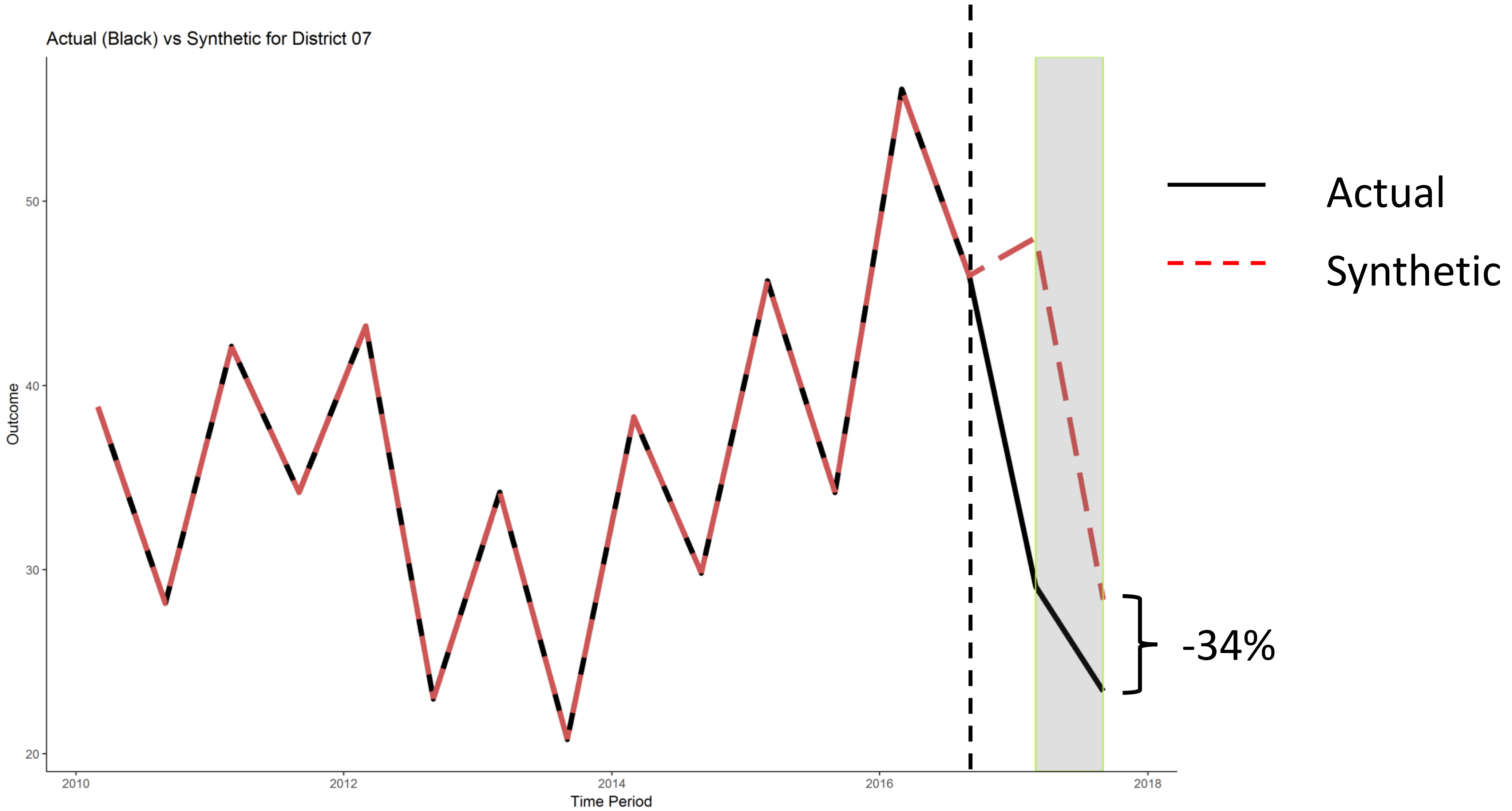
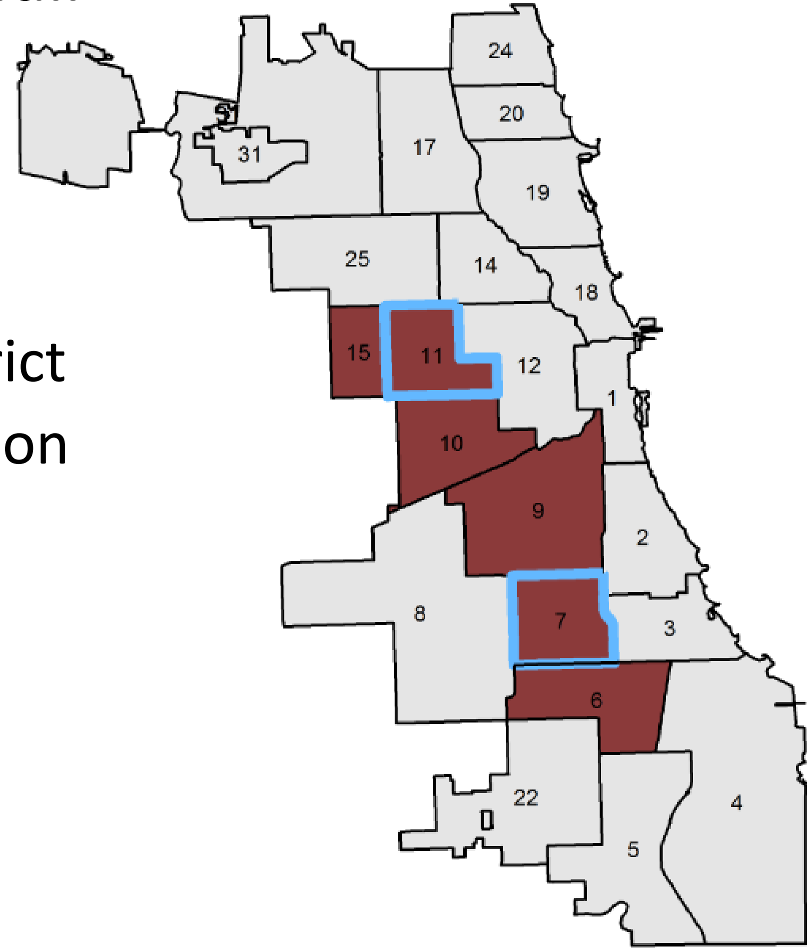


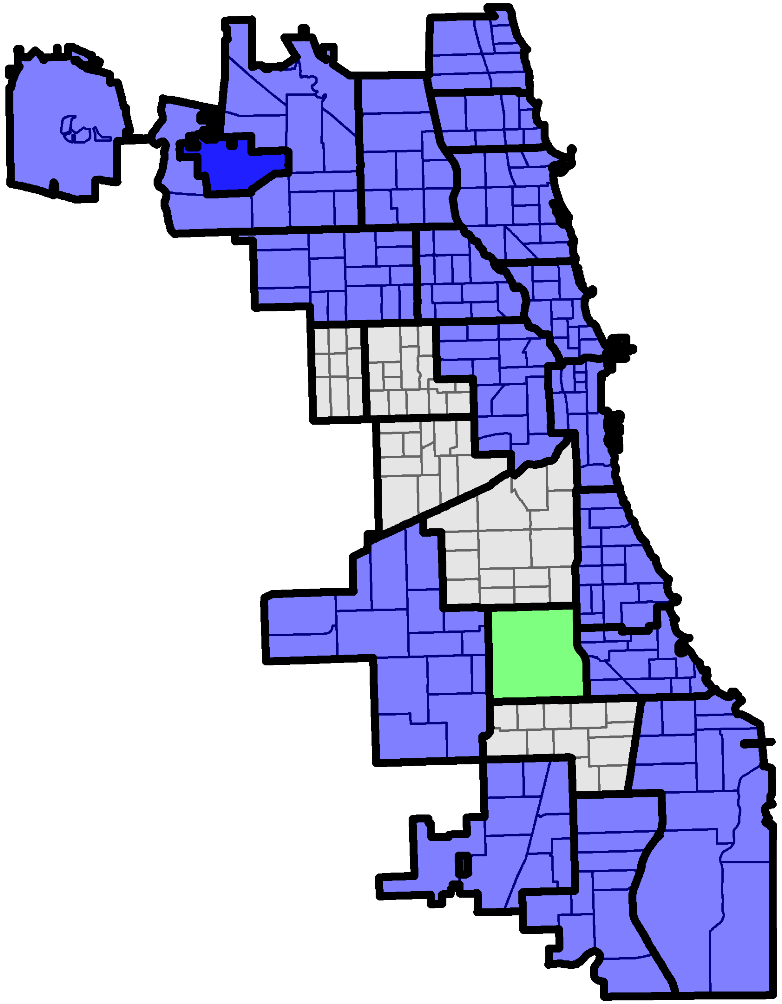
Inference: placebo-in-place

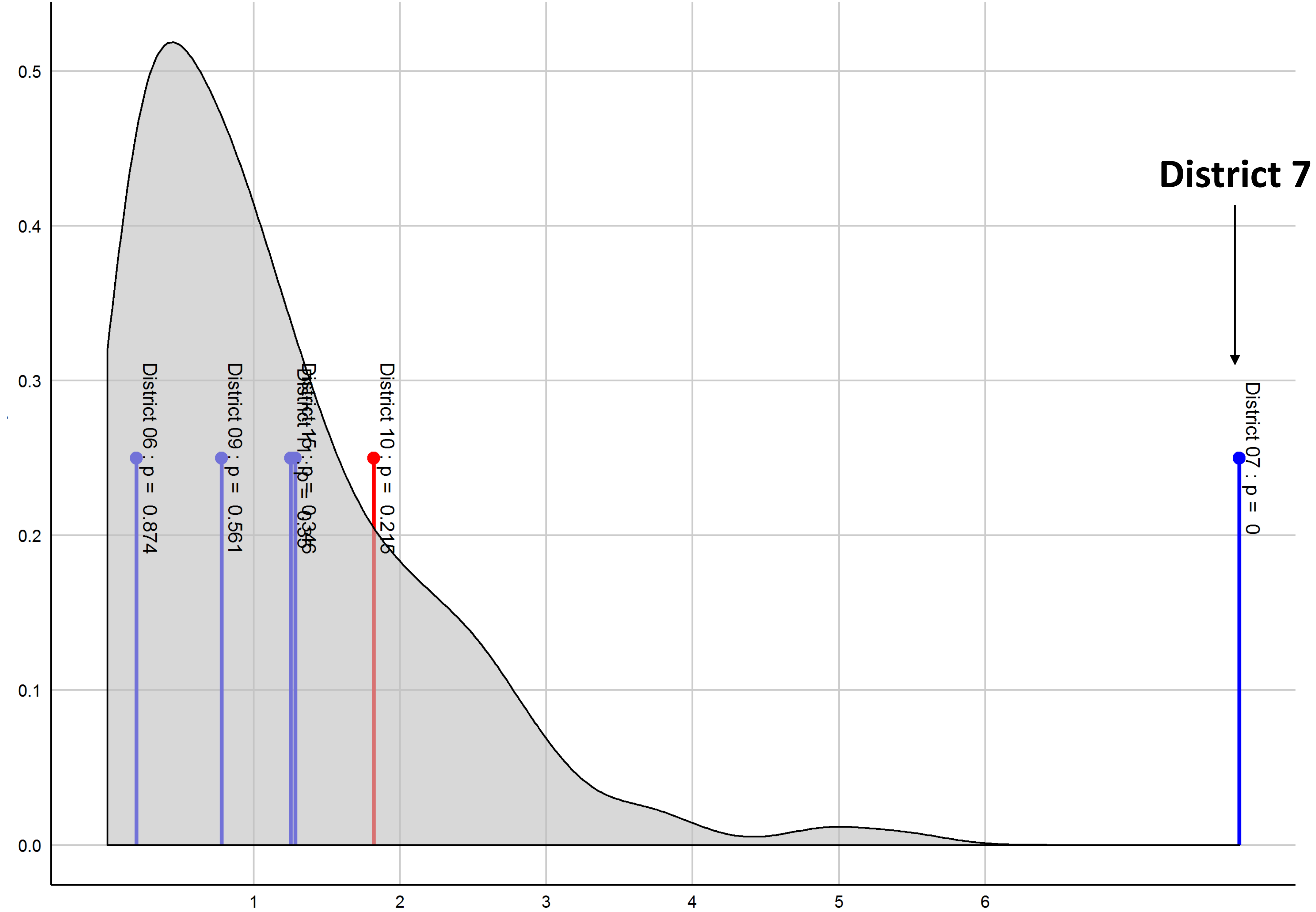
- Assess estimate's significance by comparing to null (placebo) distribution of treatment effects
- Placebo-in-place
  - Estimate synthetic counterpart for each control district
  - Compare observed test statistic to placebo distribution
- But there are only 16 non-SDSC districts
  - Up to 16 p-values = sparse placebo distribution



Inference: placebo-in-place

- Workaround: bootstrapped control districts
  - For each control district, resample N beats with replacement K times
  - K resampled districts are perturbed versions of original control district
  - Similar to method used by Robbins, Saunders, and Kilmer (2017)




District 7
District 06 : p = 0.874
District 09 : p = 0.561
District 10 : p = 0.215
District 07 : p = 0
0.5
0.4
0.3
0.2
0.1
0.0
1
2
3
4
5
6

Shooting incidents per 100,000

District	Shooting Incident Rate		
	Estimate	p-value	Adjusted p-value (Holm)
6	-4.4%	0.874	1.000
7	-34.0%	0.000	0.000
9	-15.1%	0.561	1.000
10	16.7%	0.215	1.000
11	-11.7%	0.350	1.000
15	-9.7%	0.346	1.000

Homicide victims per 100,000

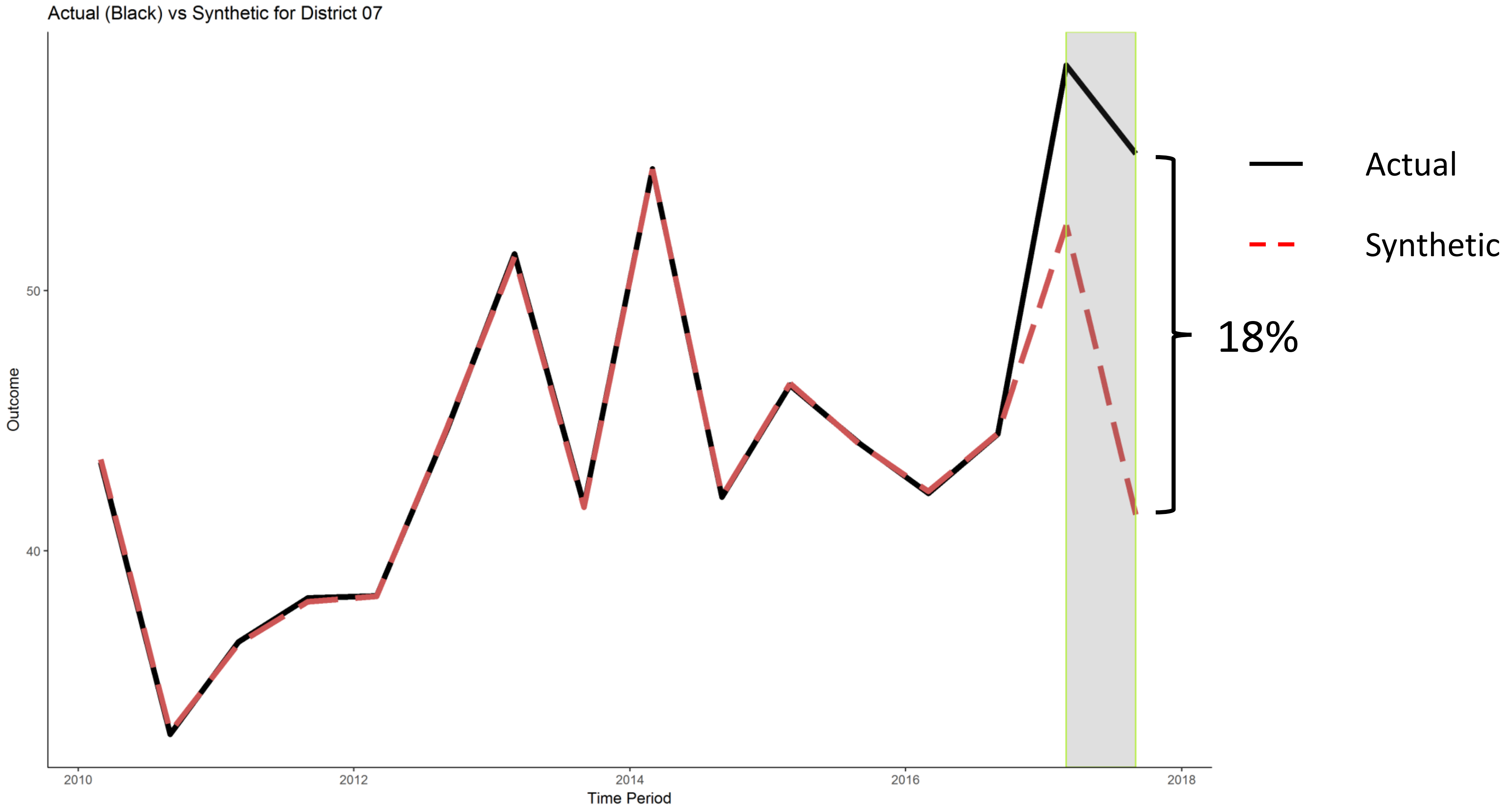
	Homicide Rate		
District	Estimate	p-value	Adjusted p-value (Holm)
6	-32.0%	0.077	0.366
7	-62.4%	0.020	0.122
9	-26.9%	0.329	0.659
10	-9.0%	0.622	0.659
11	-51.5%	0.130	0.390
15	-34.9%	0.073	0.366

Mechanisms: District 7

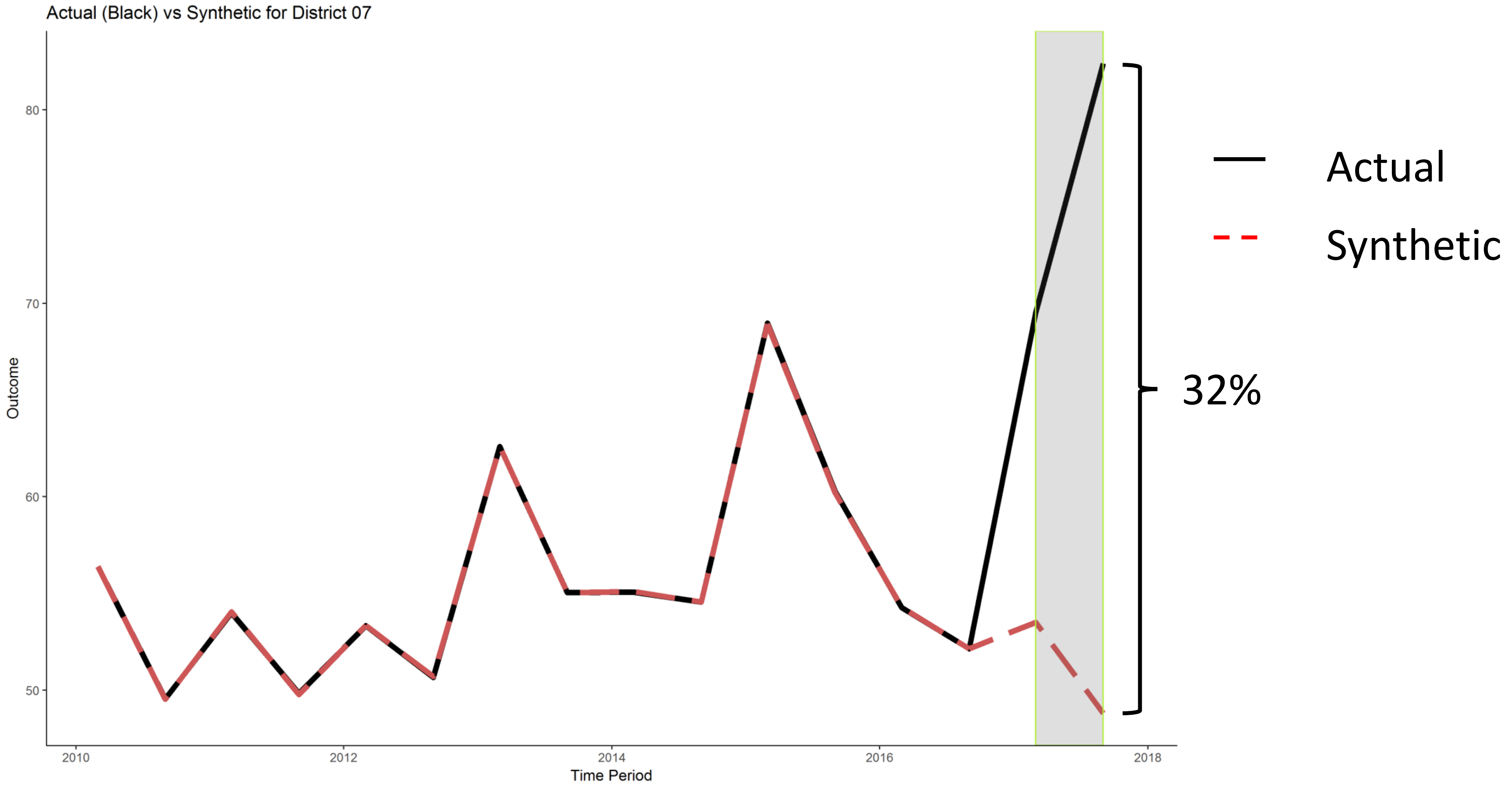
What’s behind the improvement in District 7?

- Increased **officer presence**? No
- Increased **arrests**? No
- Improved **tactics** (people, places, police-community relations)?

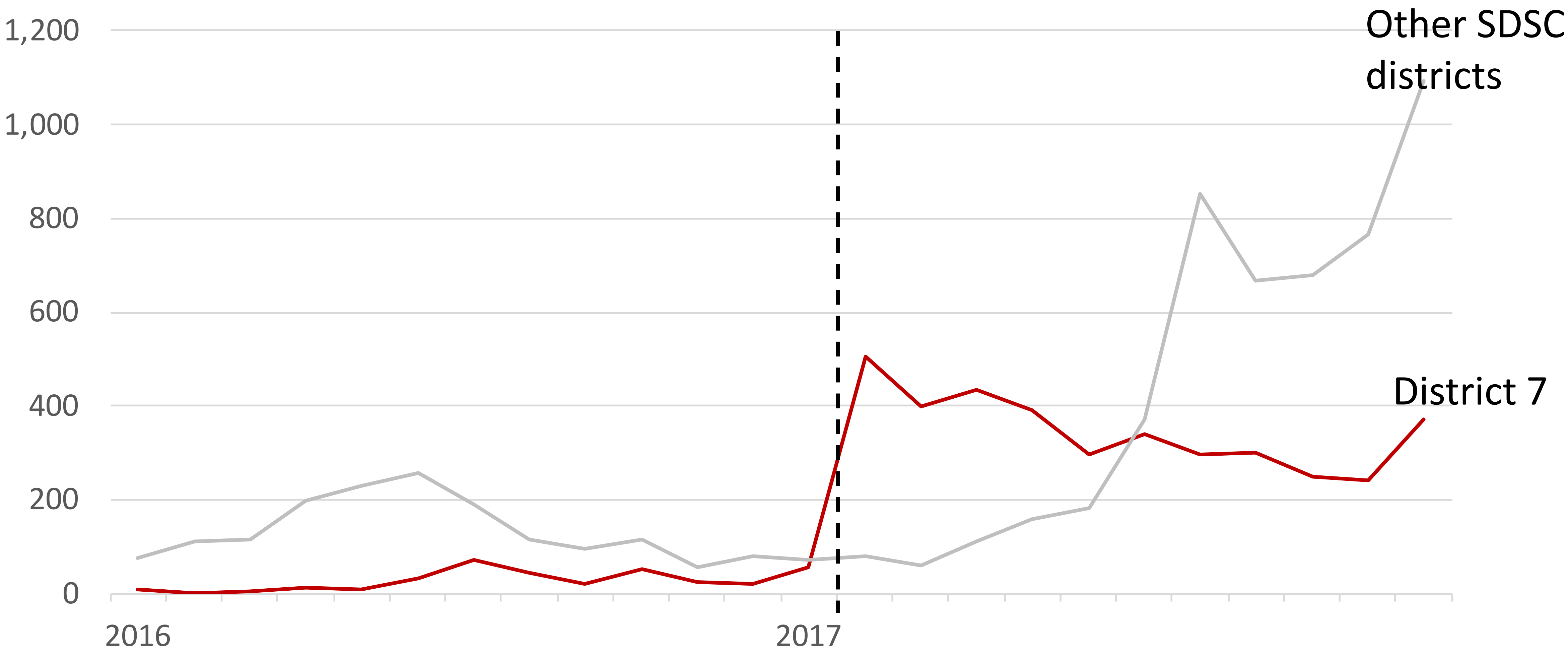
Gun arrest rate



Warrant arrest rate (tactical units)



Positive community interactions (PCIs)



What have we learned?

- Implementation as intervention
  - Echoes literature on management practices for firms (Bloom and van Reenen 2007; Syverson 2011)
  - Under-appreciated in economics of crime (and public economics generally?)

- Very cost-effective if it actually works