Policy Evaluation with Staggered Adoption

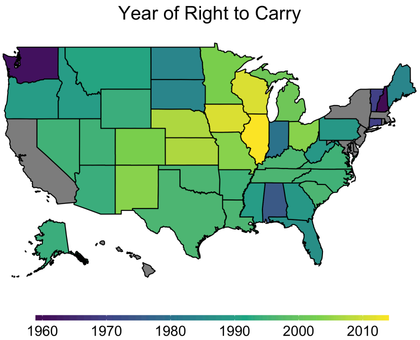
Eli Ben-Michael

Harvard University

(Based on joint work with Avi Feller, Jesse Rothstein, and Elizabeth Stuart)

What is the impact of right-to-carry laws on violent crime?

- *1959 – 2014:* 42 states enact right-to-carry



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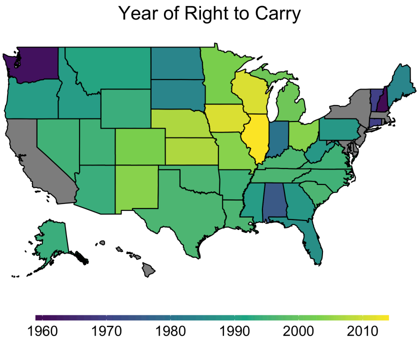
- *1959 – 2014:* 42 states enact right-to-carry
- “More guns, less crime”?
  [Lott and Mustard, 1997]



What is the impact of right-to-carry laws on violent crime?

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- “More guns, less crime”?
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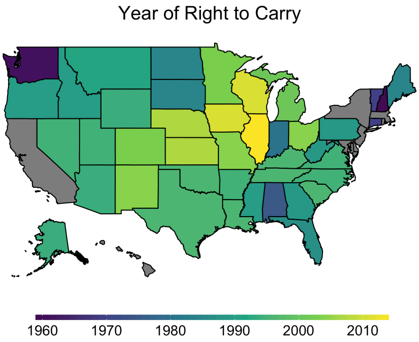
- New research says no
  [Donohue et al., 2019]



Staggered adoption: Multiple units adopt treatment over time

Estimating effects under staggered adoption

Staggered adoption: Multiple units adopt treatment over time

Common approaches can fail: Little guidance when this happens

- Difference in Differences (DiD) typical regression approach can be invalid
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A more design-based approach $\rightarrow$ **Policy Trial Emulation**

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A more design-based approach $\rightarrow$ **Policy Trial Emulation**

Applied to SCM $\rightarrow$ **Partially Pooled SCM**

- Modify optimization problem to target overall and state-specific fit
- Account for level differences with Intercept-Shifted SCM

Combining ideas from Epidemiology and Econometrics

Target Trial Emulation

Design an obs. study like a RCT

[Danaei et al., 2018;
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Panel Data Methods

Beyond two-way fixed effects

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Policy Trial Emulation

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Outcomes → What are outcomes of interest?
How do we measure them?

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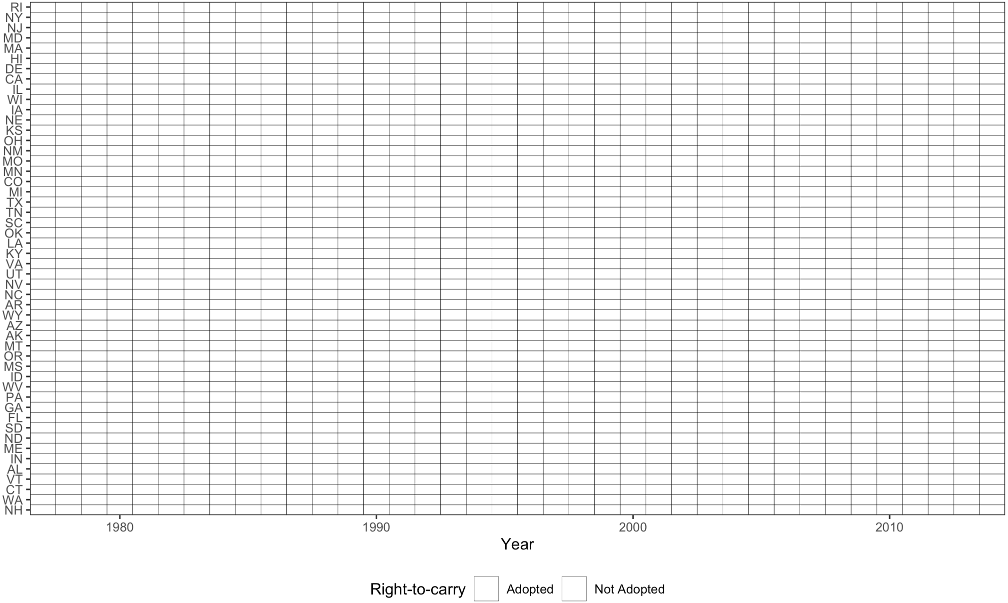
Causal Contrasts	What is the counterfactual? Does treatment start and stop?

The Elements of **Policy Trial Emulation**

Units and Exposures	→	What is treatment? Inclusion and exclusion criteria?
Outcomes	→	What are outcomes of interest? How do we measure them?
Causal Contrasts	→	What is the counterfactual? Does treatment start and stop?
Time Zero	→	What is pre-treatment? What is post-treatment?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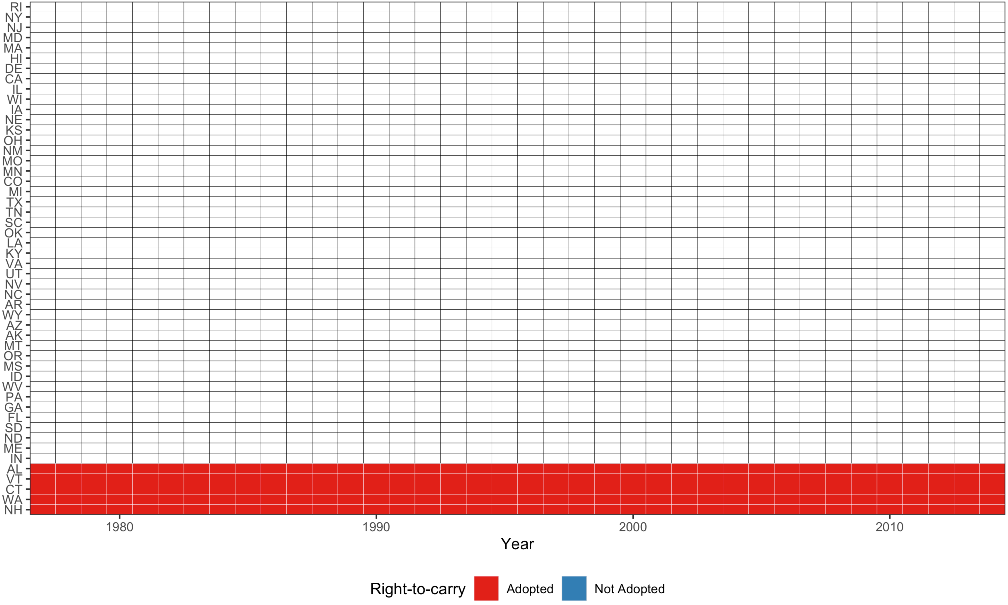
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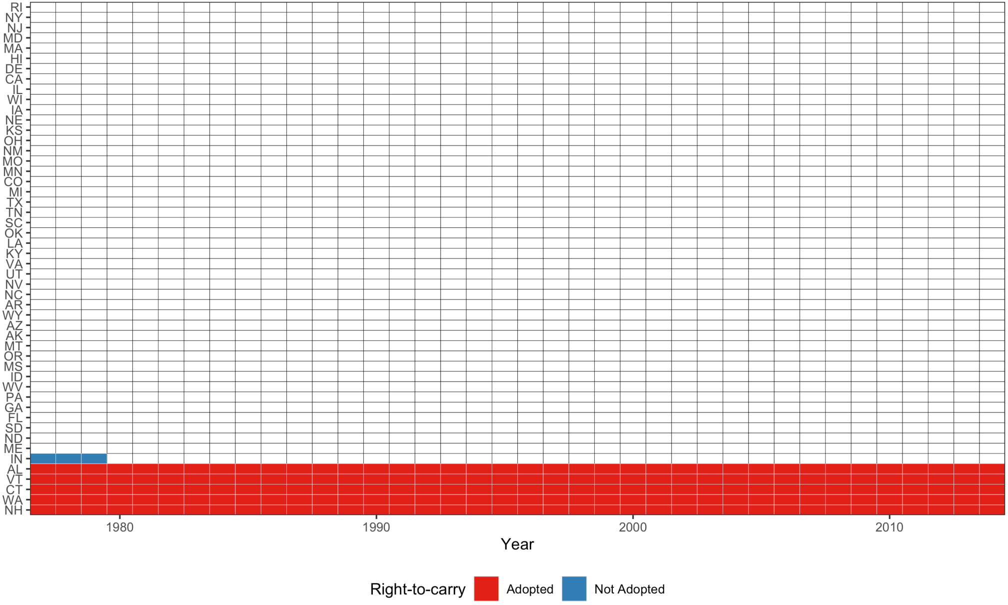
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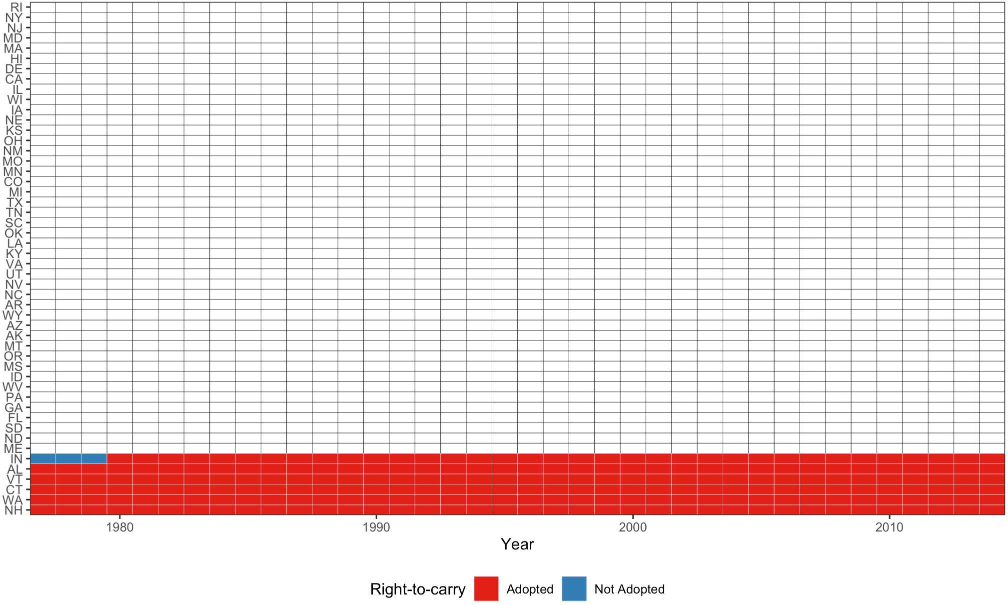
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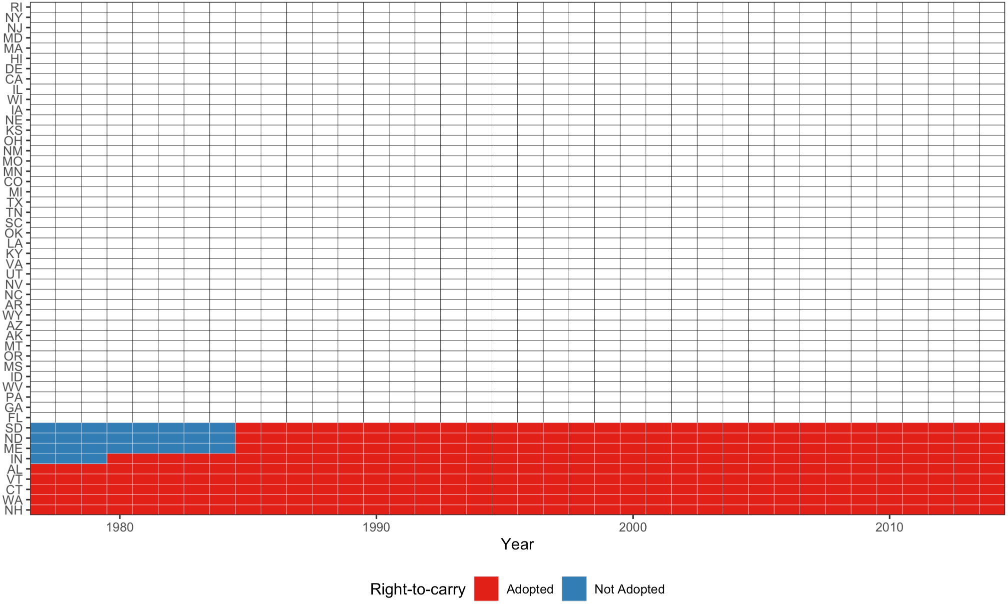
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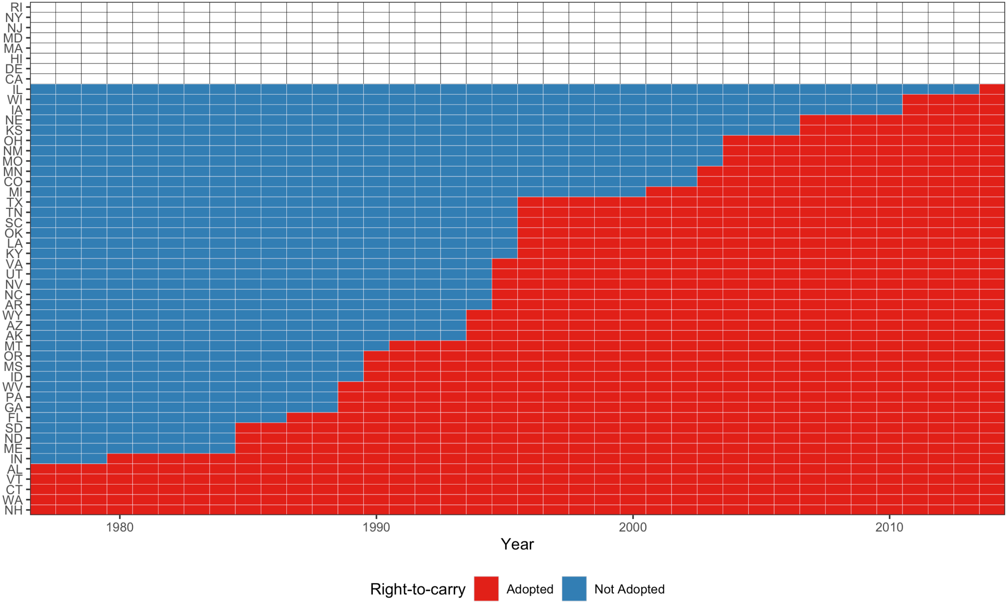
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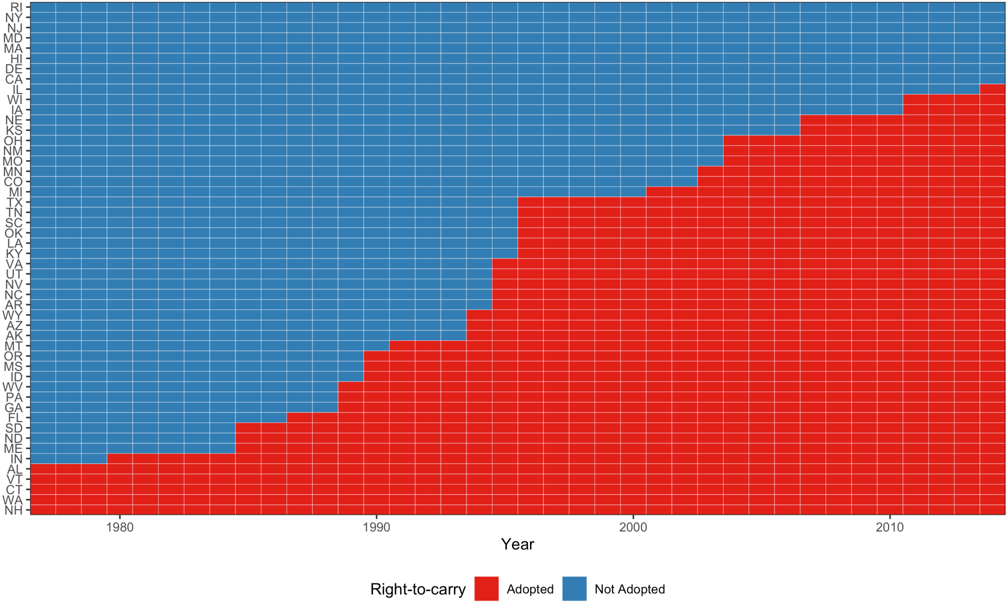
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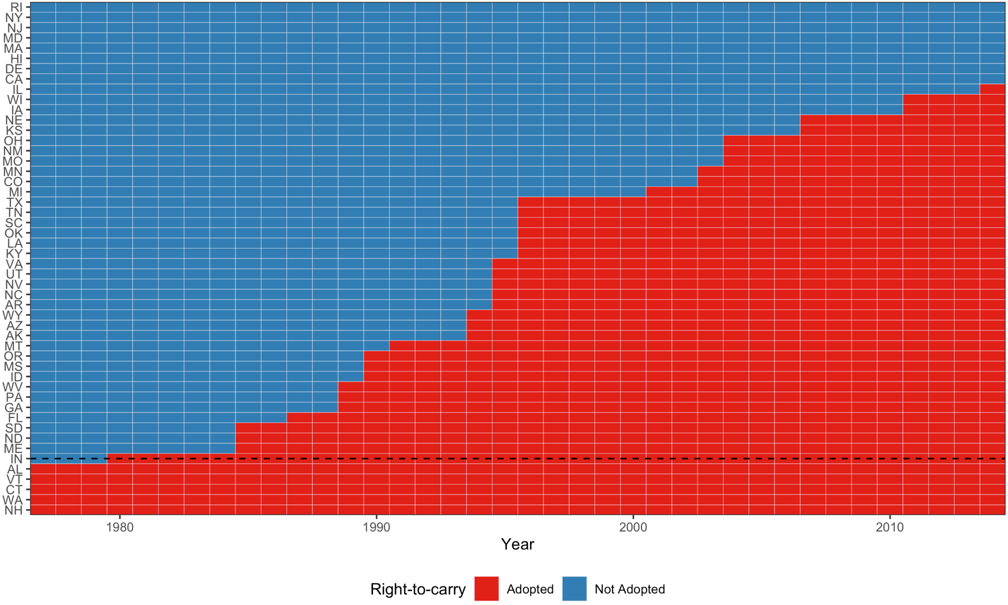
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Units: $i = 1, \ldots, N$, J total treated units

Time: $t = 1, \ldots, T$, treatment times $T_1, \ldots, T_J, \infty$

Outcome: at *event time* k, Y_{i,T_j+k}

- Some assumptions to write down potential outcomes
  [Athey and Imbens, 2018; Imai and Kim, 2019]

$$\text{treat} = \begin{pmatrix} & \checkmark & \checkmark & \checkmark \\ & & \checkmark & \checkmark \\ & & & \checkmark \\ & & & \end{pmatrix}$$

Causal contrasts

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Basic building block:

$$\tau_{jk} = Y_{jT_j+k}(T_j) \quad - \quad \underbrace{Y_{jT_j+k}(\infty)}_{\sum \hat{\gamma}_{ij} Y_{iT_j+k}}$$

Single Target Trial

Causal contrasts

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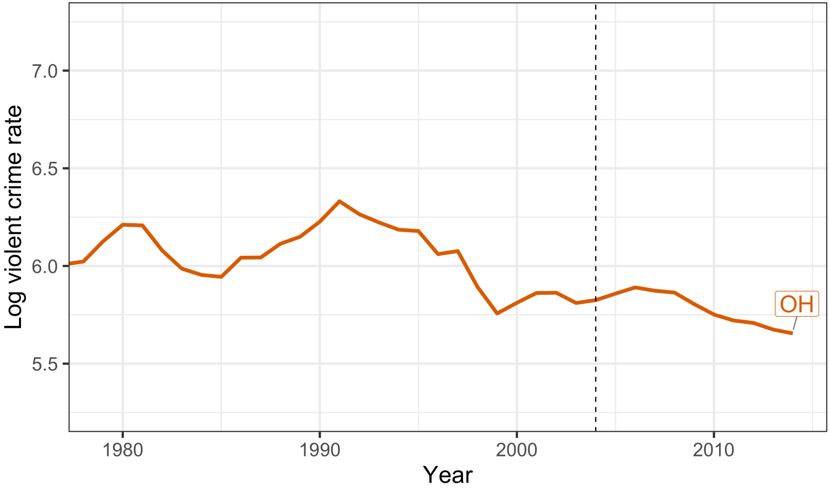
Single Target Trial

Average at event time k:

$$\text{ATT}_k = \frac{1}{J} \sum_{j=1}^{J} \tau_{jk}$$

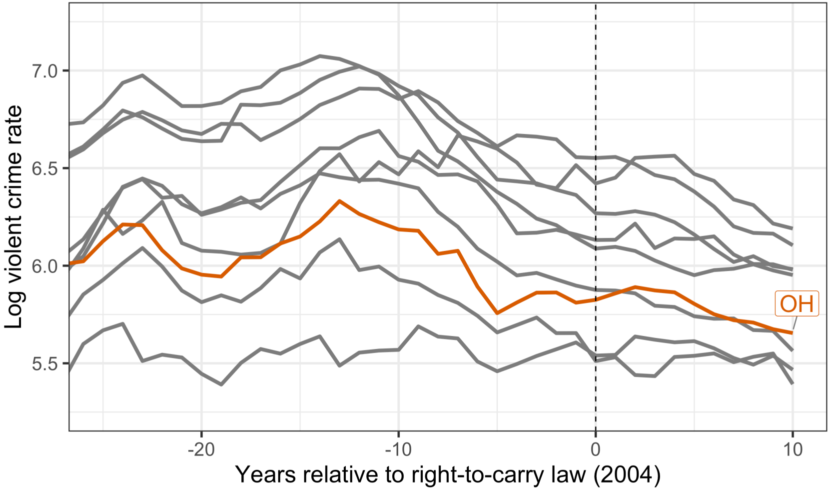
Nested Target Trials

Single Target Trial
Synthetic Controls



7.0
6.5
6.0
5.5
Log violent crime rate
1980
1990
2000
2010
Year
OH


7.0
6.5
6.0
5.5
Log violent crime rate
-20
-10
0
10
Years relative to right-to-carry law (2004)
OH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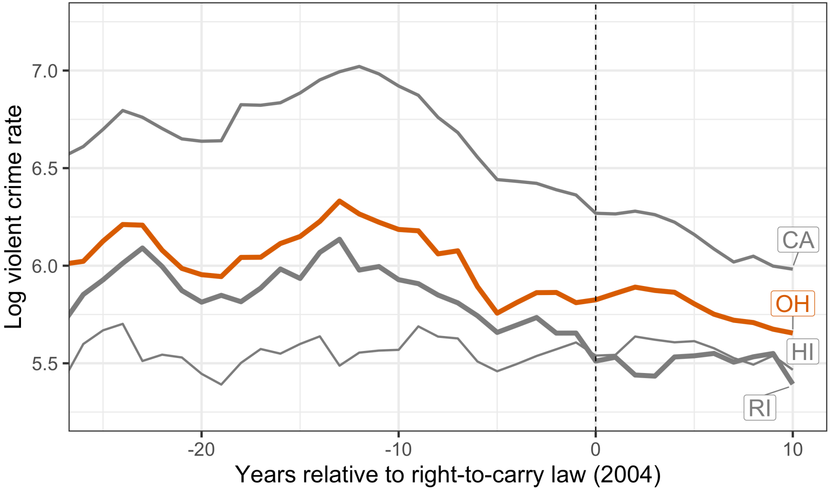
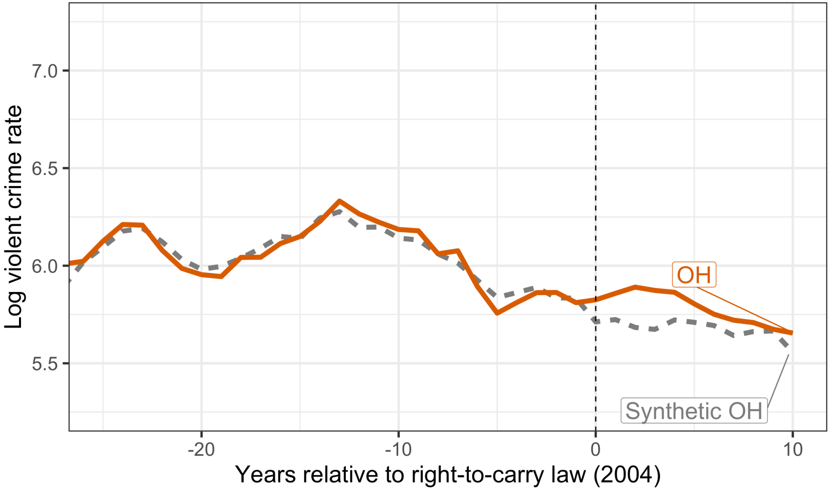


$$\min_{\gamma \in \Delta^{\mathrm{scm}}} \left\| Y_{\mathrm{OH}\ell} - \sum_{i \neq \mathrm{OH}} \gamma_i Y_{i\ell} \right\|_2^2 + \text{penalty}$$



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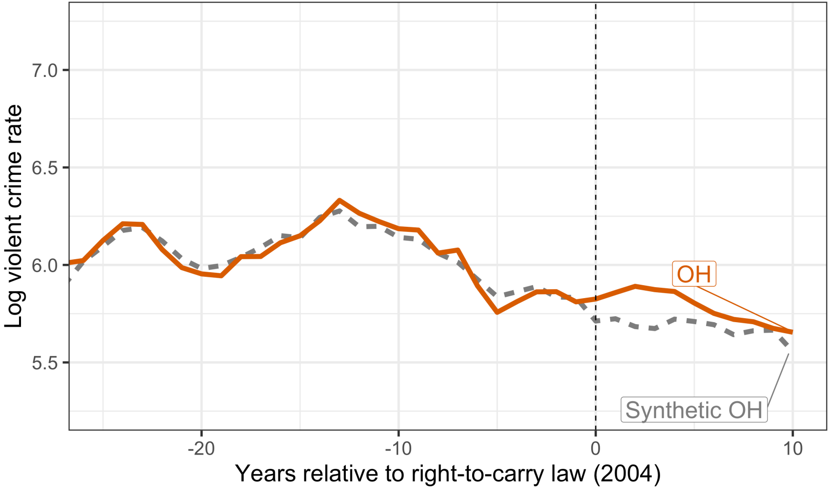
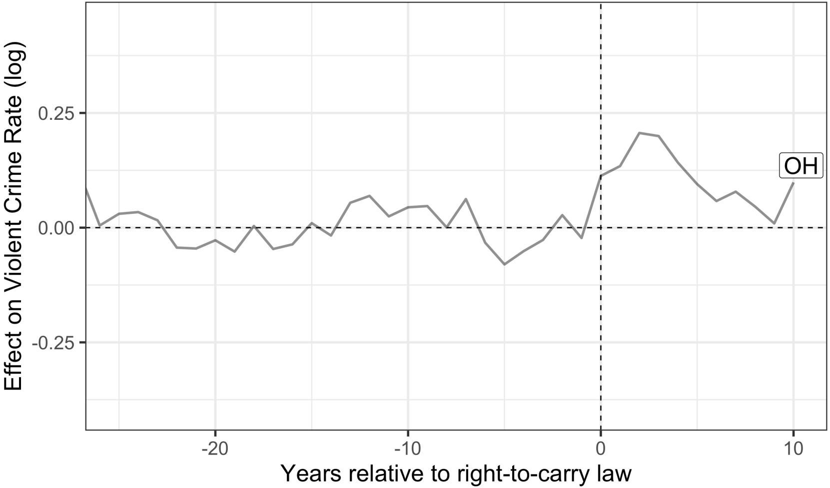


$$\min_{\gamma \in \Delta^{\text{scm}}} \quad \|\text{State Balance}\|_2^2 + \text{penalty}$$



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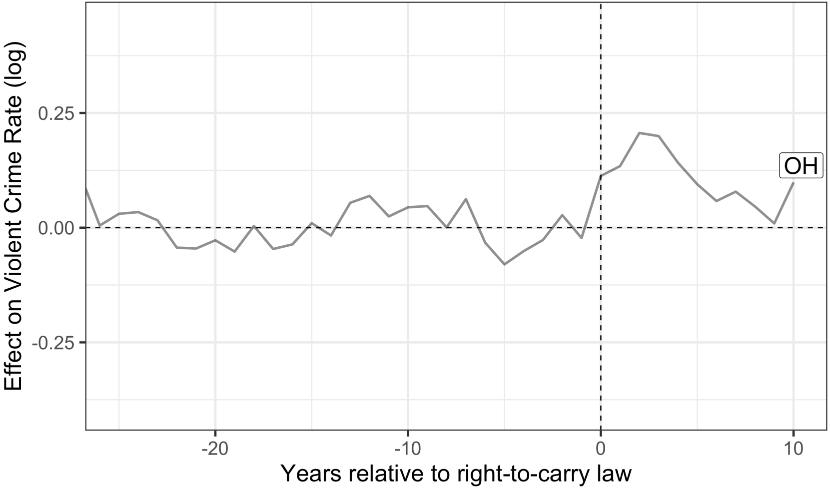
Towards Nested Target Trials
Separate Synthetic Controls



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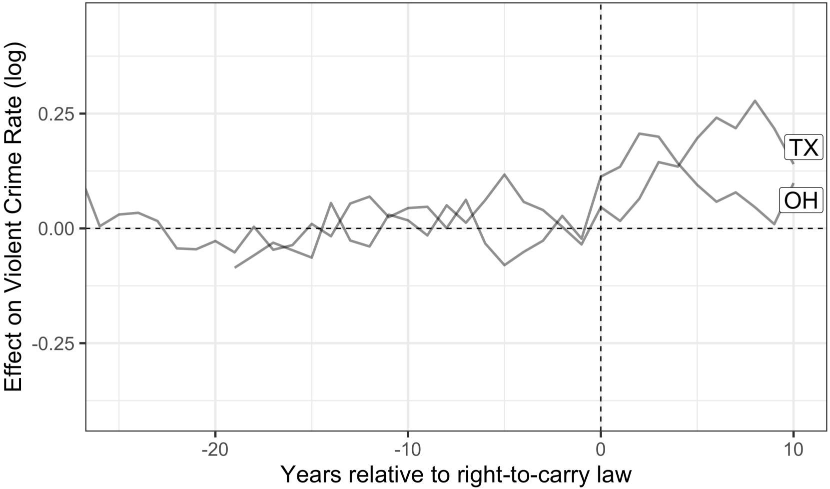
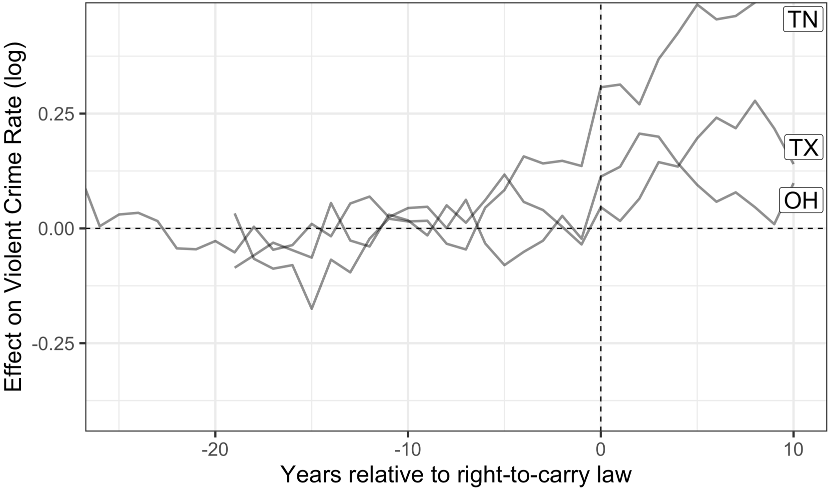


$$\min_{\Gamma \in \Delta^{\text{scm}}} \frac{1}{J} \sum_{j=1}^{J} \left\| \text{State Balance}_j \right\|_2^2 + \text{penalty}$$



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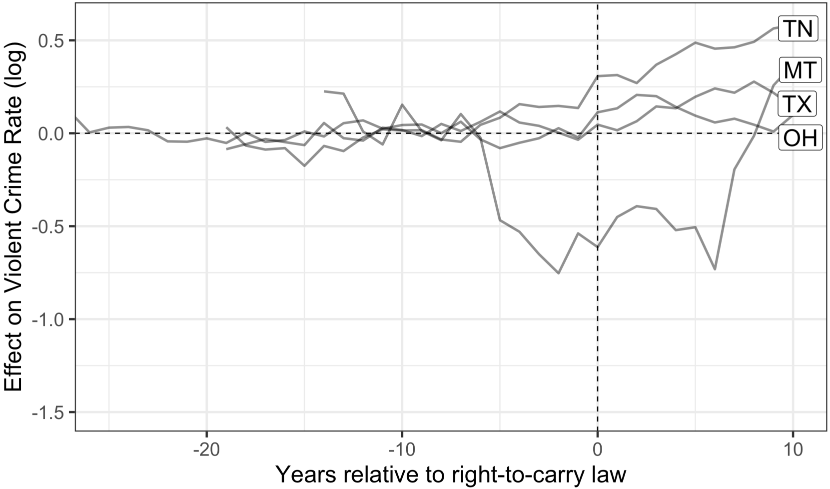

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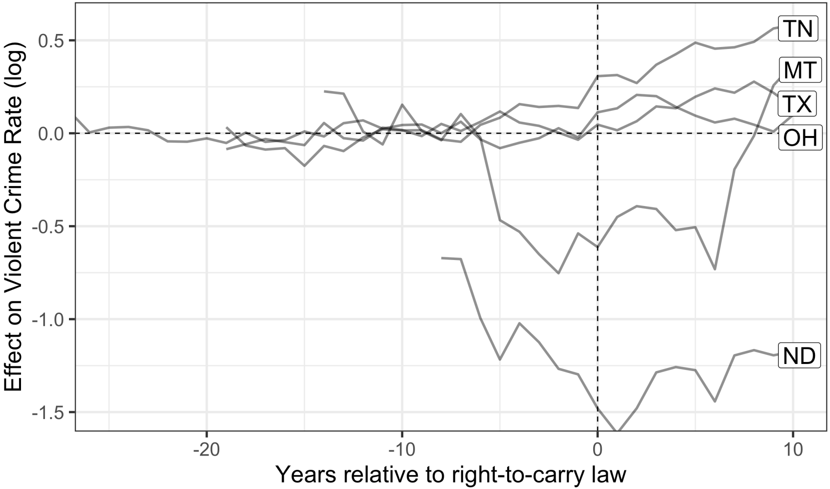

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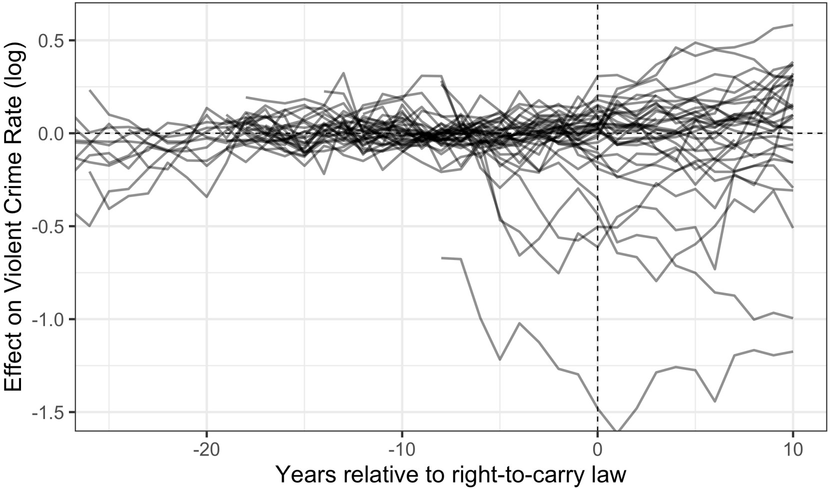

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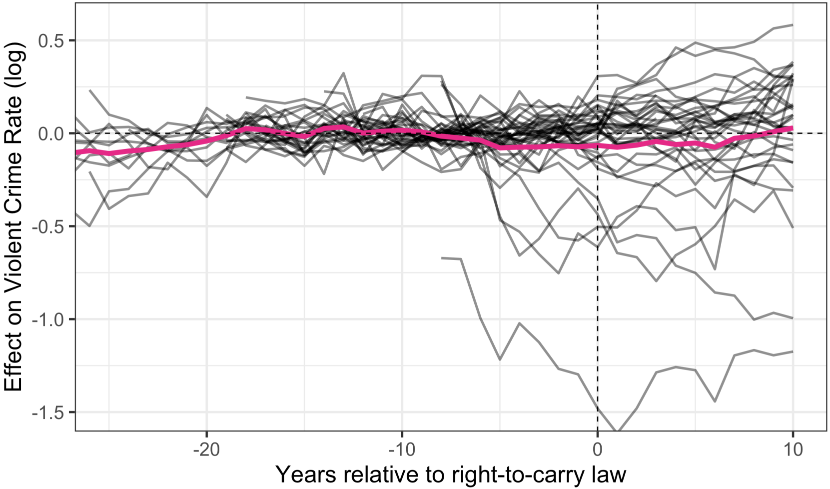

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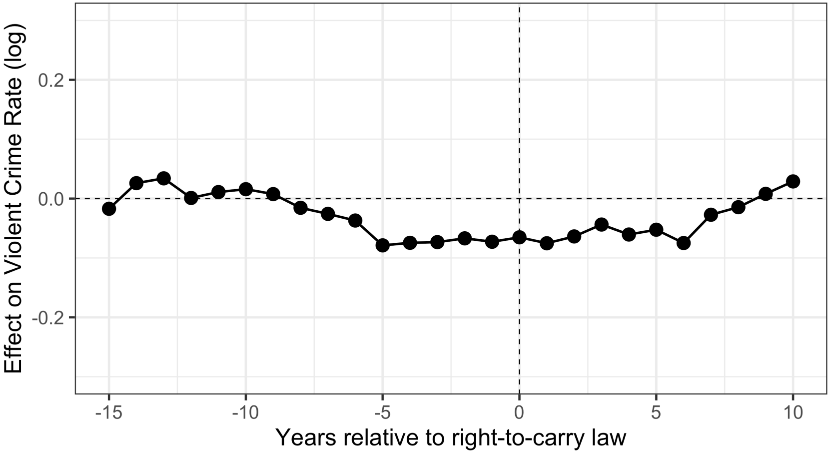
Separate SCM



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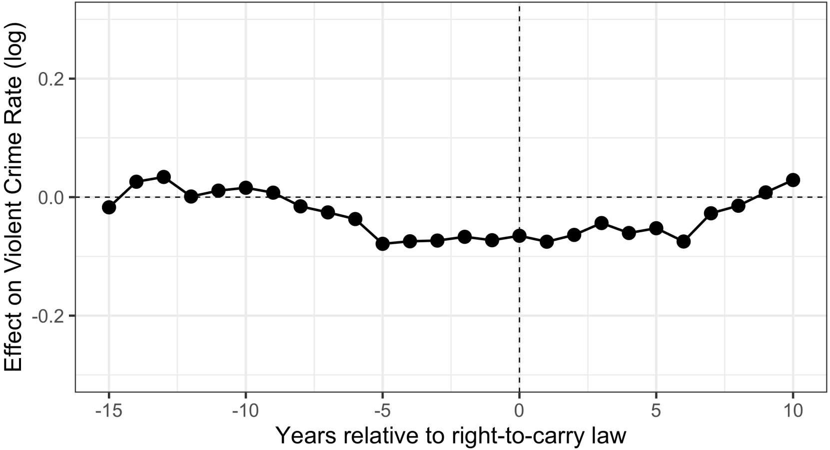
Partially Pooled SCM

Separate SCM



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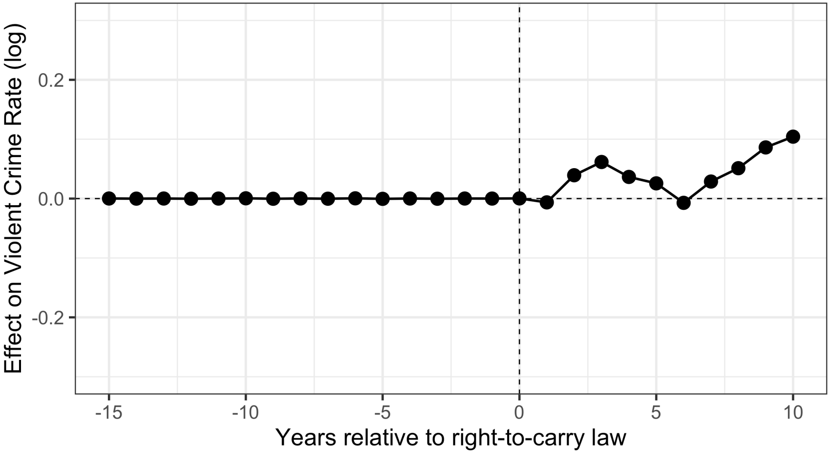
Pooled SCM



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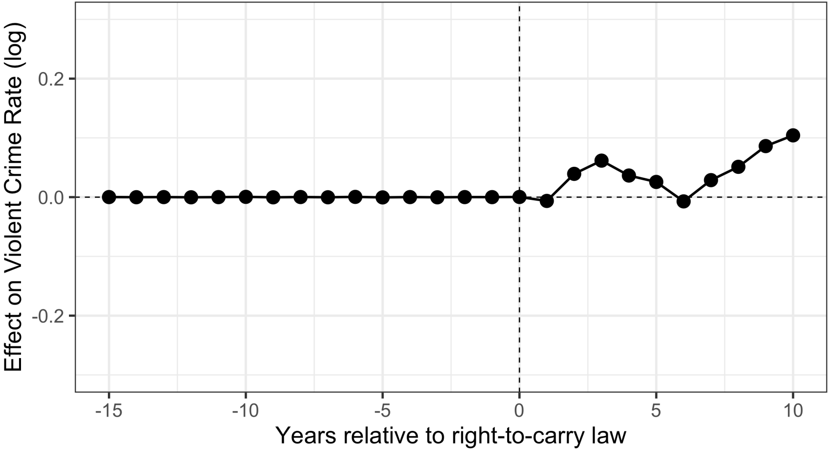
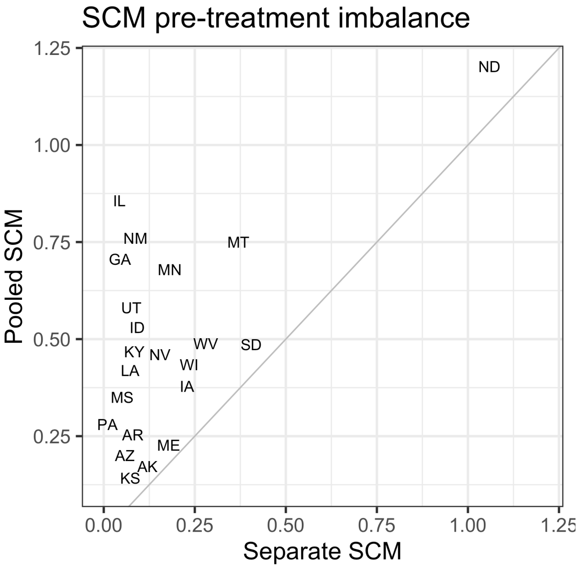
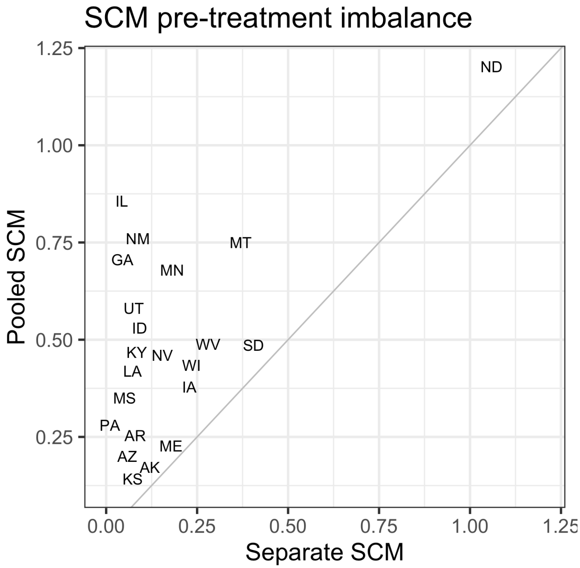
Pooled SCM



$$\min_{\Gamma \in \Delta^{\text{scm}}} \|\text{Pooled Balance}\|_2^2 + \text{penalty}$$



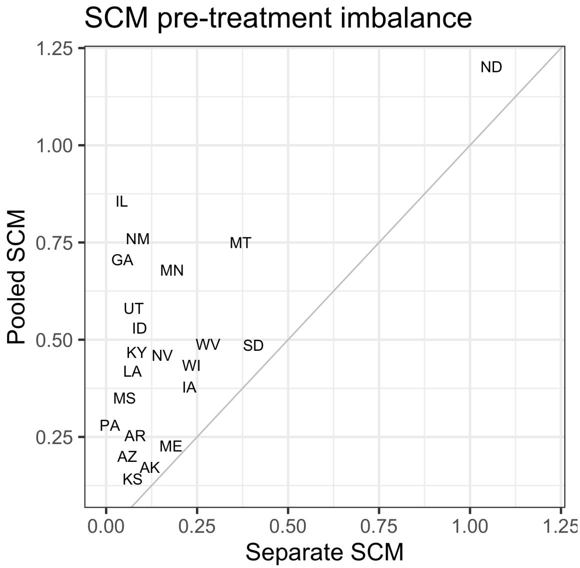
Pooled Balance is better!



Pooled Balance is better!

... but State Balance is worse

- Bad for **state estimates**



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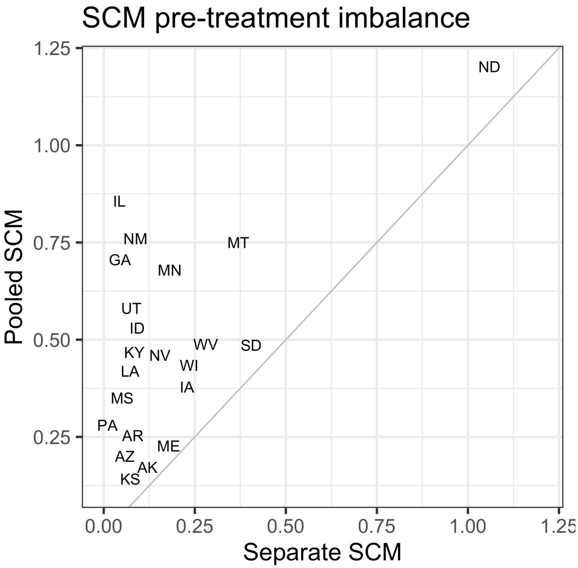
Also bad for the **average**!

- When DGP varies over time



Pooled Balance is better!

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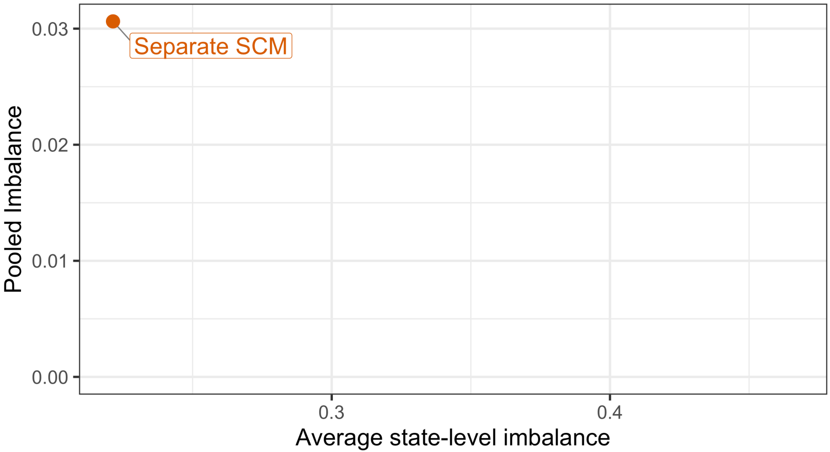
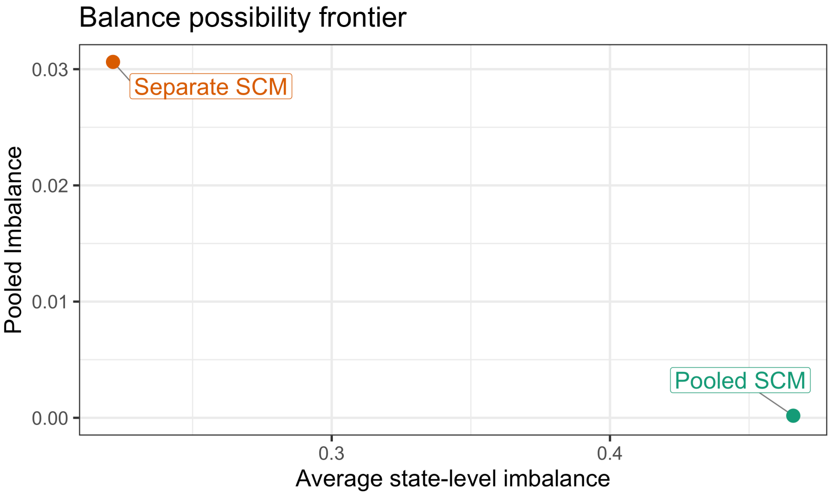
Find weights that balance both Pooled Balance and State Balance

Balance possibility frontier



$$\min_{\Gamma \in \Delta^{\text{scm}}} \quad \nu \left\| \text{Pooled Balance} \right\|_2^2 + \frac{1-\nu}{J} \sum_{j=1}^{J} \left\| \text{State Balance}_j \right\|_2^2 + \text{penalty}$$



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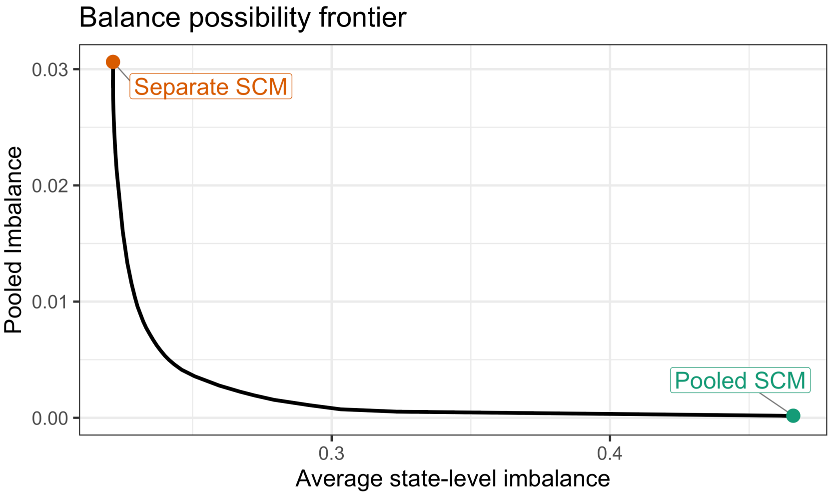
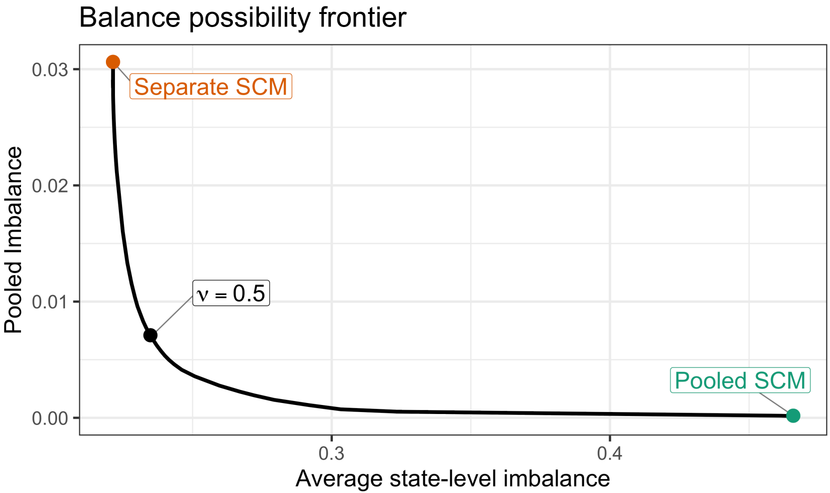
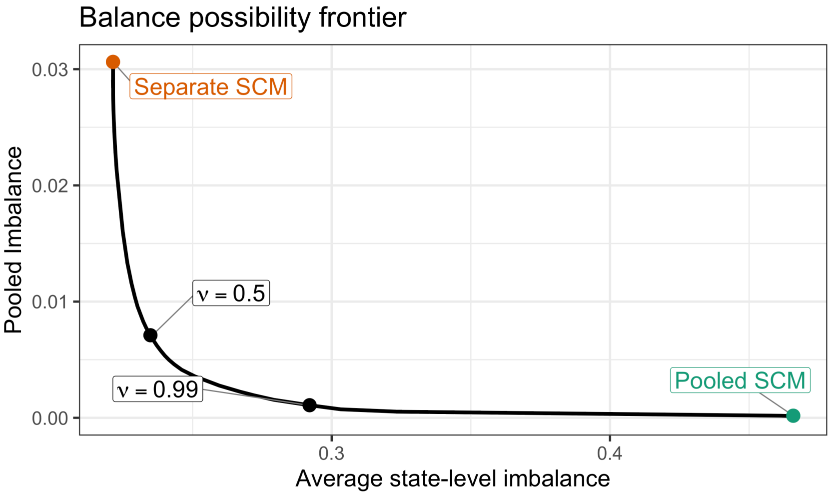


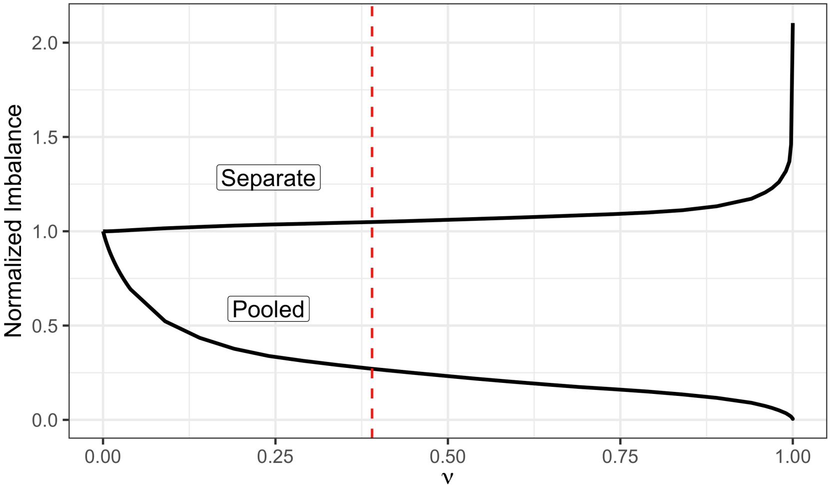
$$\min_{\Gamma \in \Delta^{\text{scm}}} \quad \nu \left\|\text{Pooled Balance}\right\|_2^2 + \frac{1-\nu}{J} \sum_{j=1}^{J} \left\|\text{State Balance}_j\right\|_2^2 + \text{penalty}$$



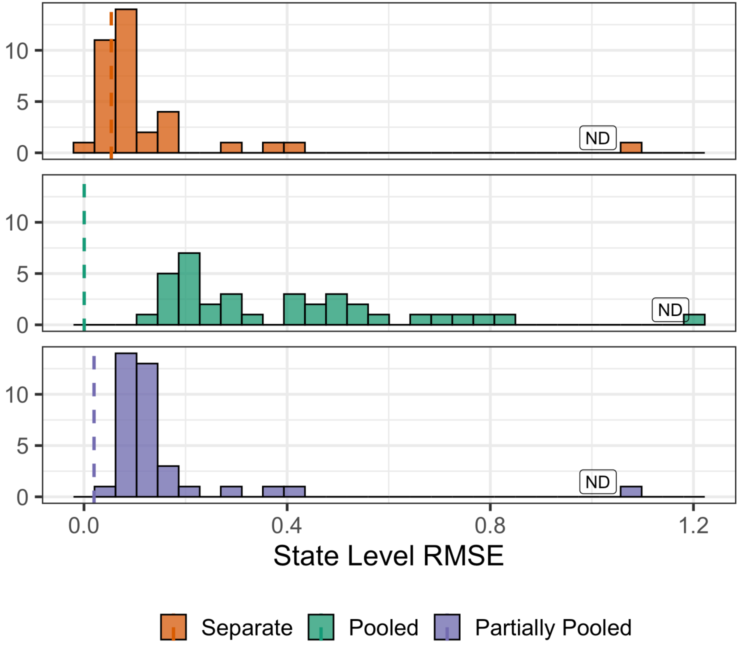
$$\min_{\Gamma \in \Delta^{\text{scm}}} \quad \nu \, \left\| \text{Pooled Balance} \right\|_2^2 + \frac{1-\nu}{J} \sum_{j=1}^{J} \left\| \text{State Balance}_j \right\|_2^2 + \text{penalty}$$



$$\min_{\Gamma \in \Delta^{scm}} \quad \nu \left\| \text{Pooled Balance} \right\|_2^2 + \frac{1-\nu}{J} \sum_{j=1}^{J} \left\| \text{State Balance}_j \right\|_2^2 + \text{penalty}$$

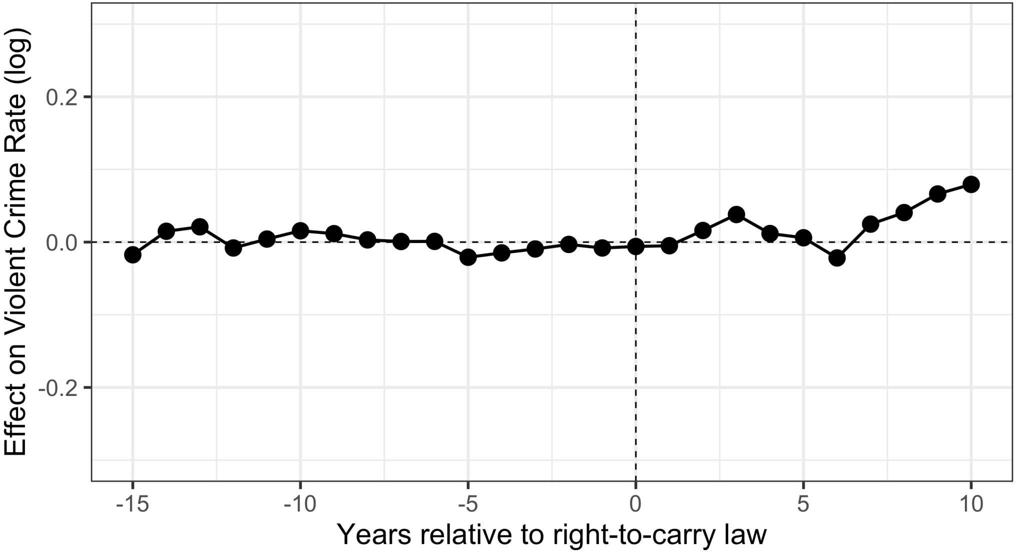


$$\text{Heuristic for } \nu = \frac{\|\text{Pooled Balance}\|_2}{\frac{1}{\sqrt{J}}\sum_{j=1}^{J} \|\text{State Balance}_j\|_2} \qquad \text{fit with } \nu = 0$$



10
5
0
ND
10
5
0
ND
10
5
0
ND
0.0
0.4
0.8
1.2
State Level RMSE
Separate
Pooled
Partially Pooled

Partially Pooled SCM



Extensions

Intercept-Shifted SCM

Adjust for level differences by adding an intercept to the optimization problem

[Doudchenko and Imbens, 2017; Ferman and Pinto, 2018]

$$\hat{Y}^{*}_{j,T_j+k}(\infty) = \hat{\alpha}_j + \sum_{i} \hat{\gamma}^{*}_{ij} Y_{i,T_j+k}$$

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Solution: De-meaning by pre-treatment average $\bar{Y}^{\text{pre}}_{i,T_j}$

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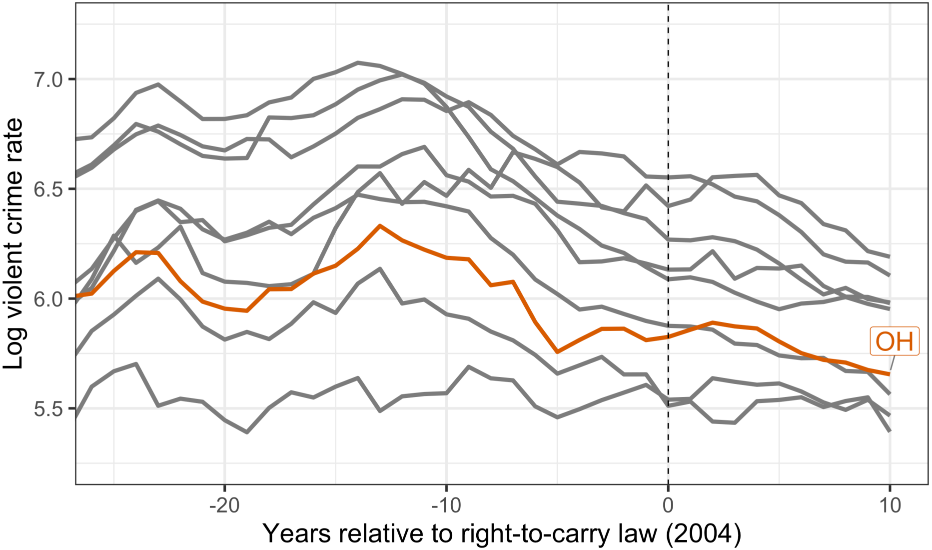
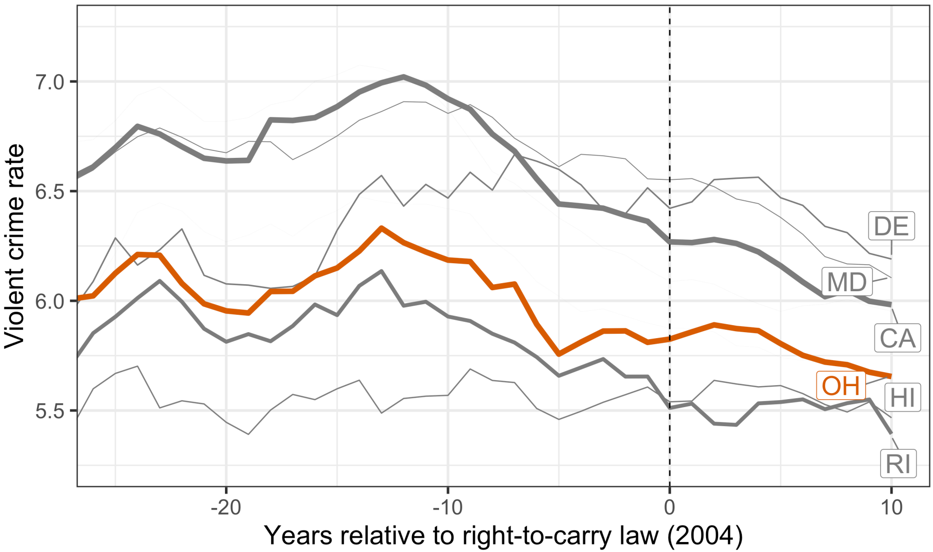
Solution: De-meaning by pre-treatment average $\bar{Y}^{\text{pre}}_{i,T_j}$

Treatment effect estimate is **weighted difference-in-differences**

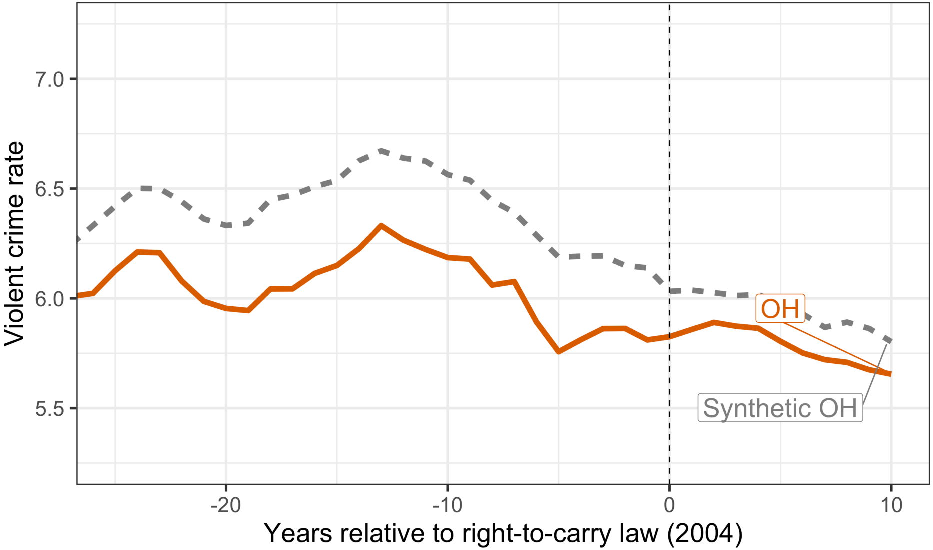
$$\hat{\tau}_{jk} = \left(Y_{j,T_j+k} - \bar{Y}^{\text{pre}}_{j,T_j}\right) - \sum_{i=1}^{N} \hat{\gamma}^*_{ij} \left(Y_{i,T_j+k} - \bar{Y}^{\text{pre}}_{i,T_j}\right)$$

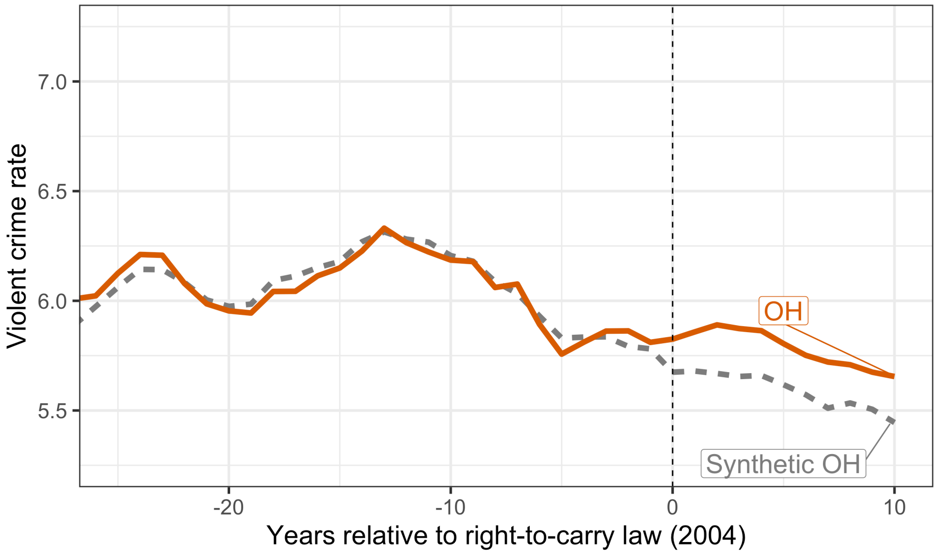
- → Uniform weights recover "stacked" DiD [Abraham and Sun, 2018]
- → Similar in form to P-score weighted DiD [Abadie, 2005; Callaway and Sant'Anna, 2020]


7.0
6.5
6.0
5.5
Log violent crime rate
-20
-10
0
10
Years relative to right-to-carry law (2004)
OH

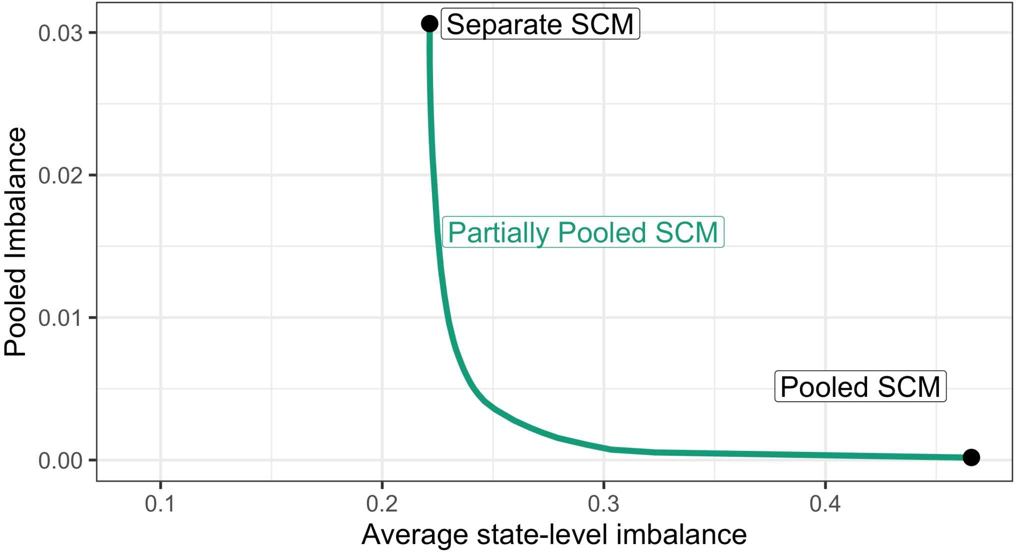


Violent crime rate
7.0
6.5
6.0
5.5
-20
-10
0
10
Years relative to right-to-carry law (2004)
DE
MD
CA
OH
HI
RI

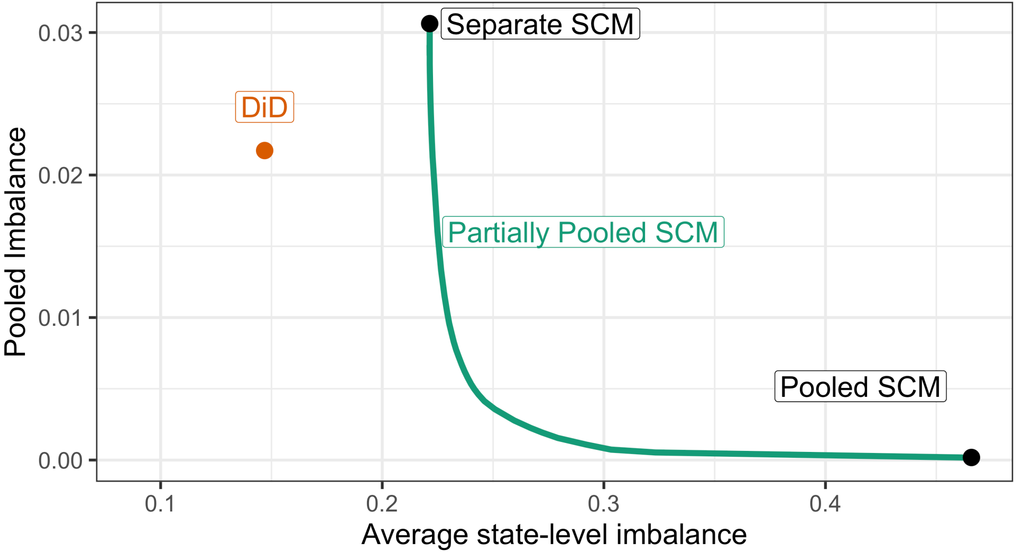

Violent crime rate
7.0
6.5
6.0
5.5
-20
-10
0
10
Years relative to right-to-carry law (2004)
OH
Synthetic OH


Violent crime rate
7.0
6.5
6.0
5.5
-20
-10
0
10
Years relative to right-to-carry law (2004)
OH
Synthetic OH

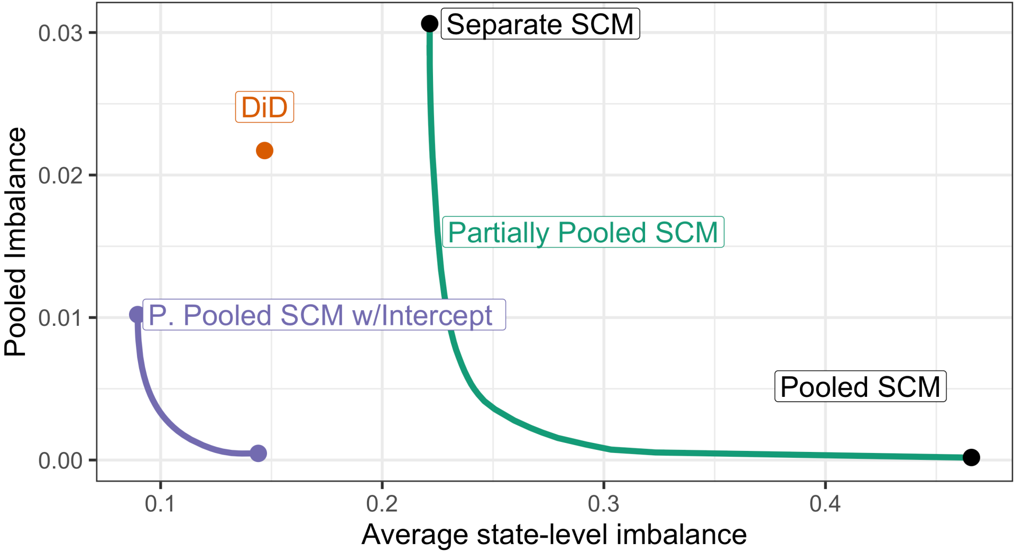
Balance possibility frontier



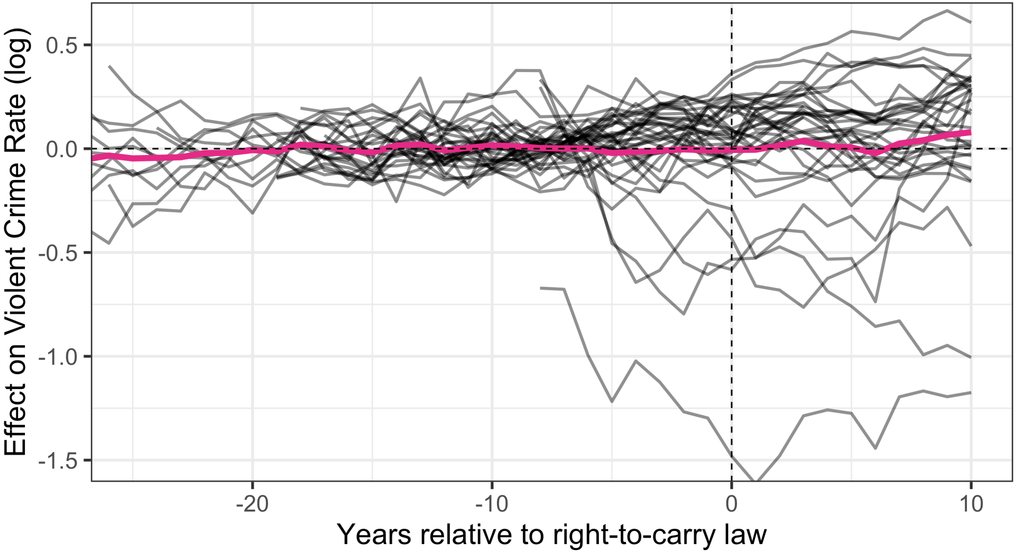
Balance possibility frontier

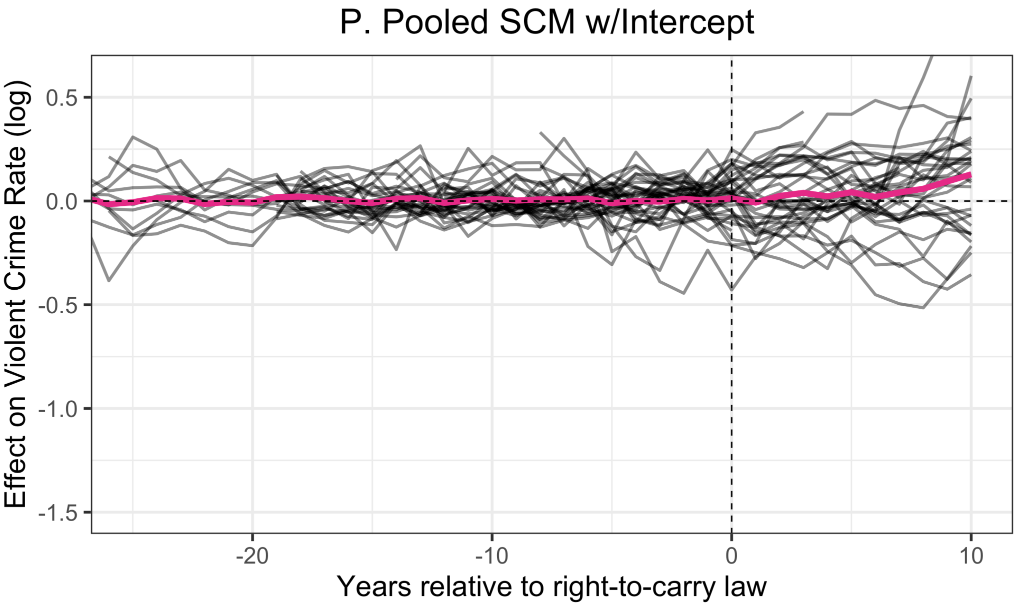


Balance possibility frontier

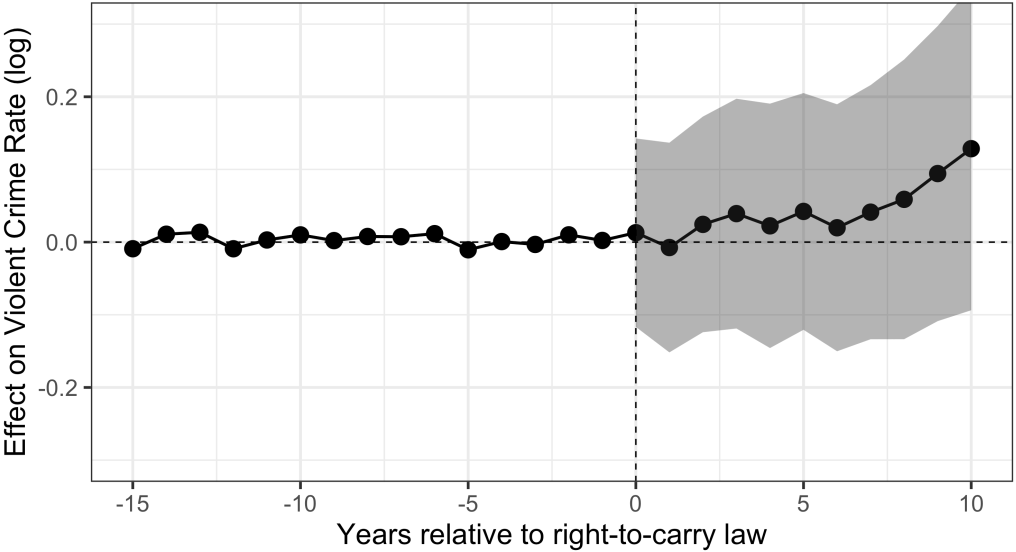


Partially Pooled SCM




P. Pooled SCM w/Intercept
Effect on Violent Crime Rate (log)
0.5
0.0
-0.5
-1.0
-1.5
-20
-10
0
10
Years relative to right-to-carry law

P. Pooled SCM w/Intercept

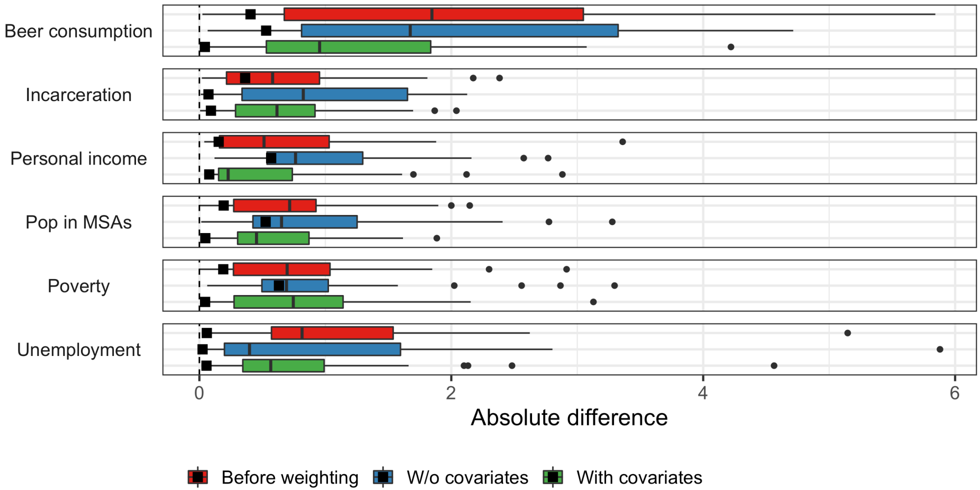


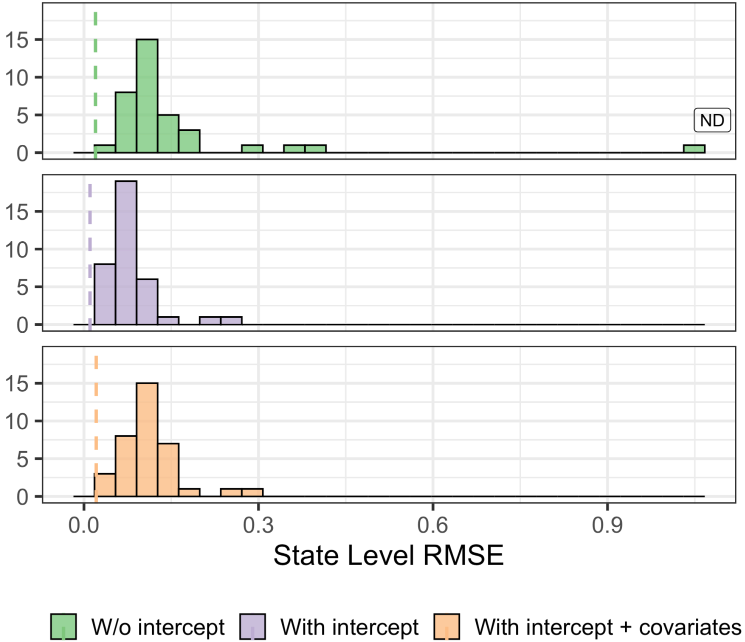
Often have additional covariates other than the main outcome

- E.g. poverty, unemployment, incarceration, and police staffing rates
- Demographics

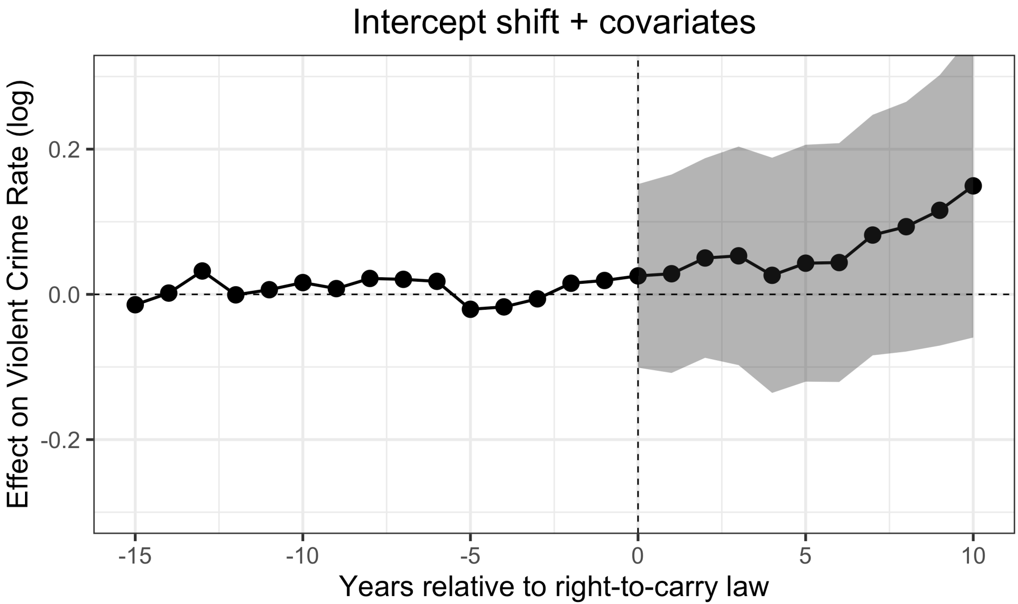
Same trade-off between State Balance and Pooled Balance

We focus on fixed covariates, but time-varying covariates are similar


Beer consumption
Incarceration
Personal income
Pop in MSAs
Poverty
Unemployment
0
2
4
6
Absolute difference
Before weighting
W/o covariates
With covariates



ND
15
10
5
0
0.0
0.3
0.6
0.9
State Level RMSE
W/o intercept
With intercept
With intercept + covariates



Intercept shift + covariates
Effect on Violent Crime Rate (log)
0.2
0.0
-0.2
-15
-10
-5
0
5
10
Years relative to right-to-carry law

Recap

Many policies we care about have **staggered adoption**

- Need to be careful when estimating effects!

A design-based approach helps clarify the issues

Applying these notions to SCM with staggered adoption

- Find weights that control State Balance and Pooled Balance
- Include an intercept to adjust for level differences
- Incorporate auxiliary covariates

Recap

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A design-based approach helps clarify the issues

Applying these notions to SCM with staggered adoption

- Find weights that control State Balance and Pooled Balance
- Include an intercept to adjust for level differences
- Incorporate auxiliary covariates

Thank you!

Synthetic Controls with Staggered Adoption

A trial emulation approach for policy evaluations with group-level longitudinal data

`https://github.com/ebenmichael/augsynth`

Appendix

The role of State Balance and Pooled Balance

Generalization of parallel trends: Linear Factor Model

$$Y_{it}(\infty) = \phi_i' \mu_t + \varepsilon_{it}$$

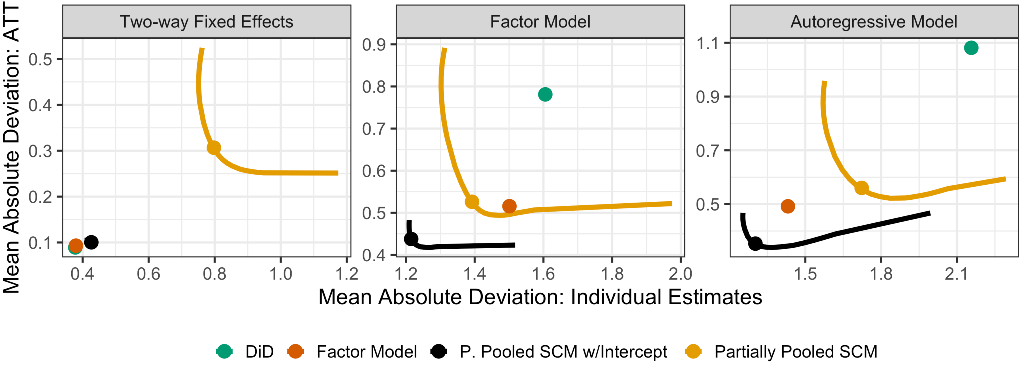
Error for ATT

$$\left|\widehat{\text{ATT}}_0 - \text{ATT}_0\right| \lesssim \|\bar{\mu}\|_2 \|\text{Pooled Balance}\|_2 + S\sqrt{\sum_{j=1}^{J} \|\text{State Balance}_j\|_2^2} + \sqrt{\frac{\log NJ}{T}}$$

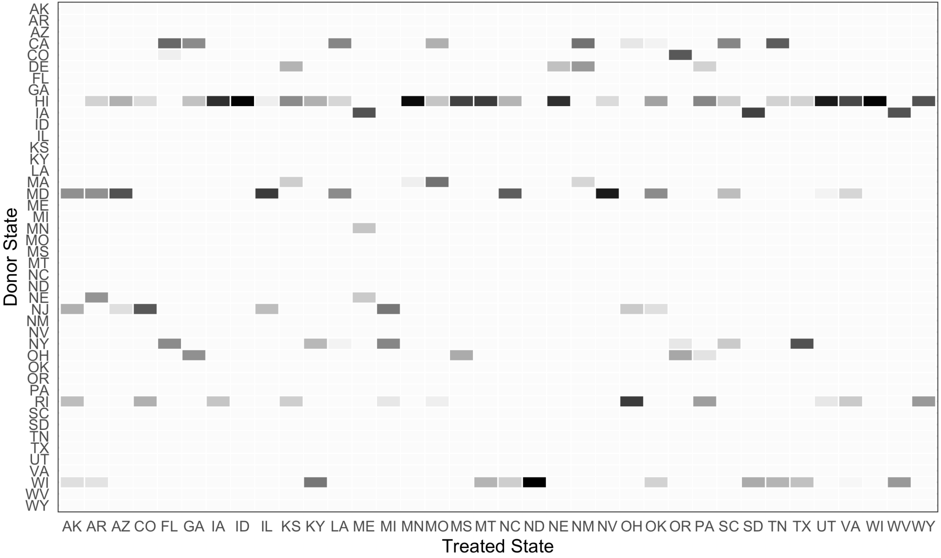
Level of **heterogeneity over time** is important

- $\bar{\mu}$ is the average factor value $\rightarrow$ importance of Pooled Balance
- S is the factor standard deviation $\rightarrow$ importance of State Balance
- Special case: unit fixed effects, only Pooled Balance matters

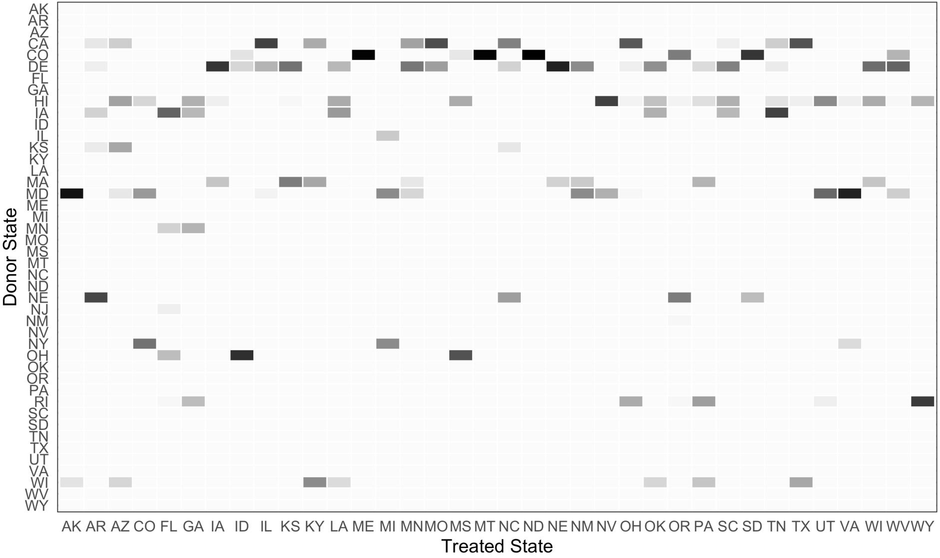
Simulation study

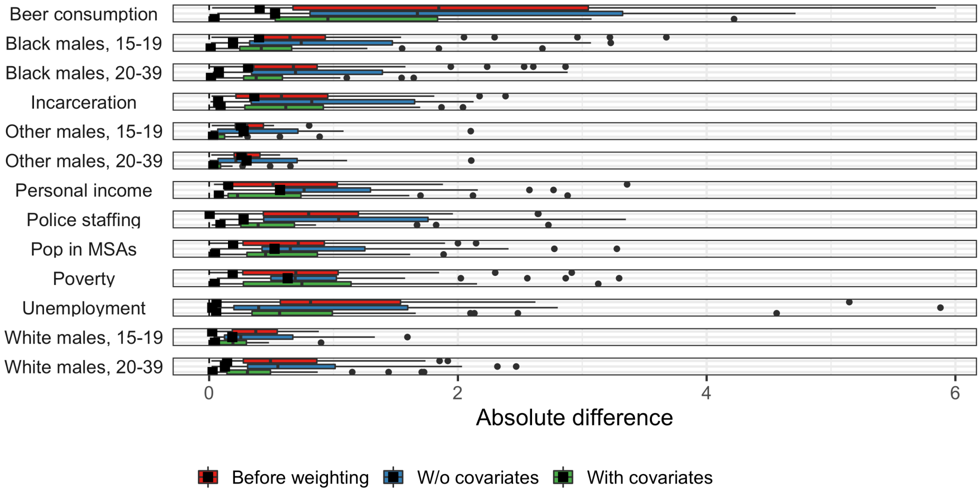


Partially pooled SCM weights

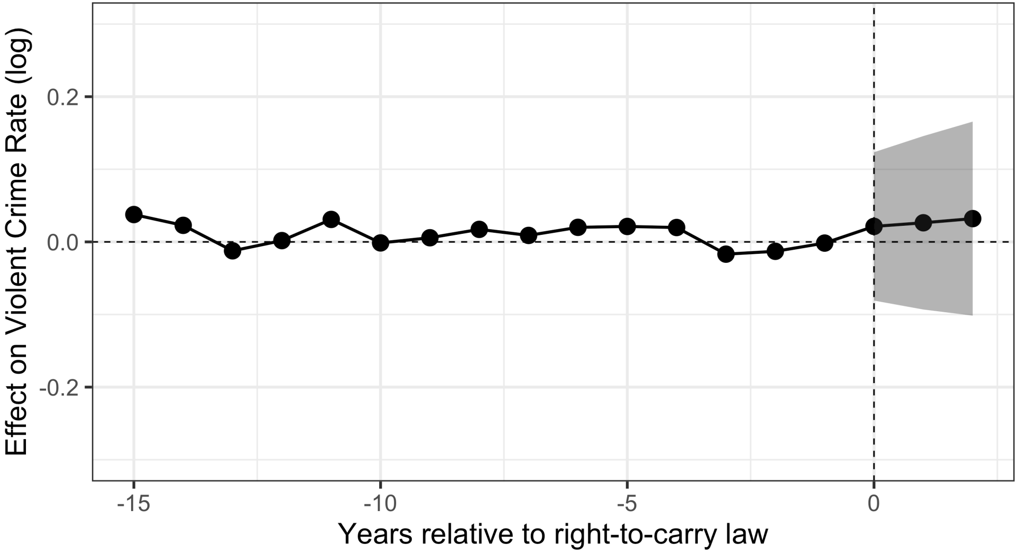


Weights with intercept

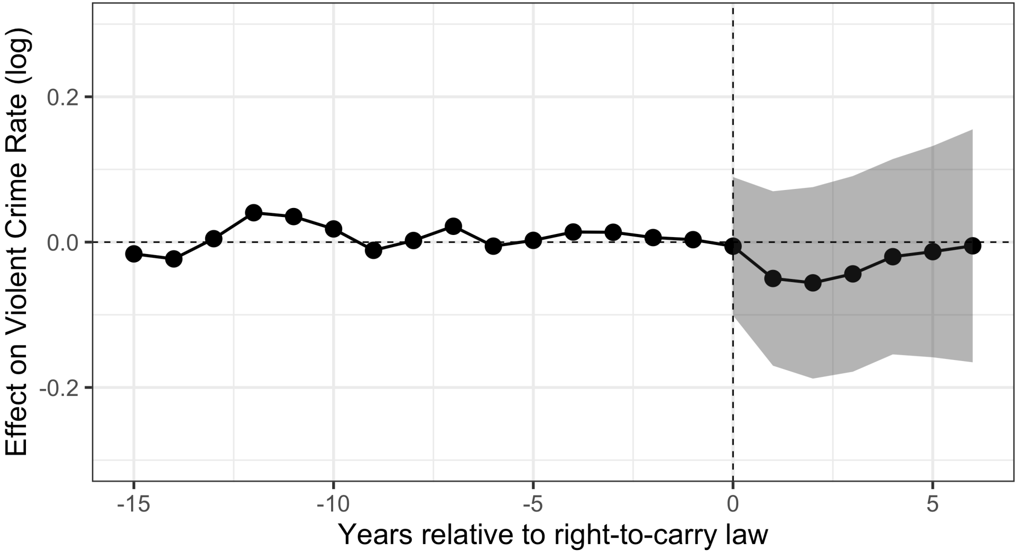



Beer consumption
Black males, 15-19
Black males, 20-39
Incarceration
Other males, 15-19
Other males, 20-39
Personal income
Police staffing
Pop in MSAs
Poverty
Unemployment
White males, 15-19
White males, 20-39
0
2
4
6
Absolute difference
Before weighting
W/o covariates
With covariates

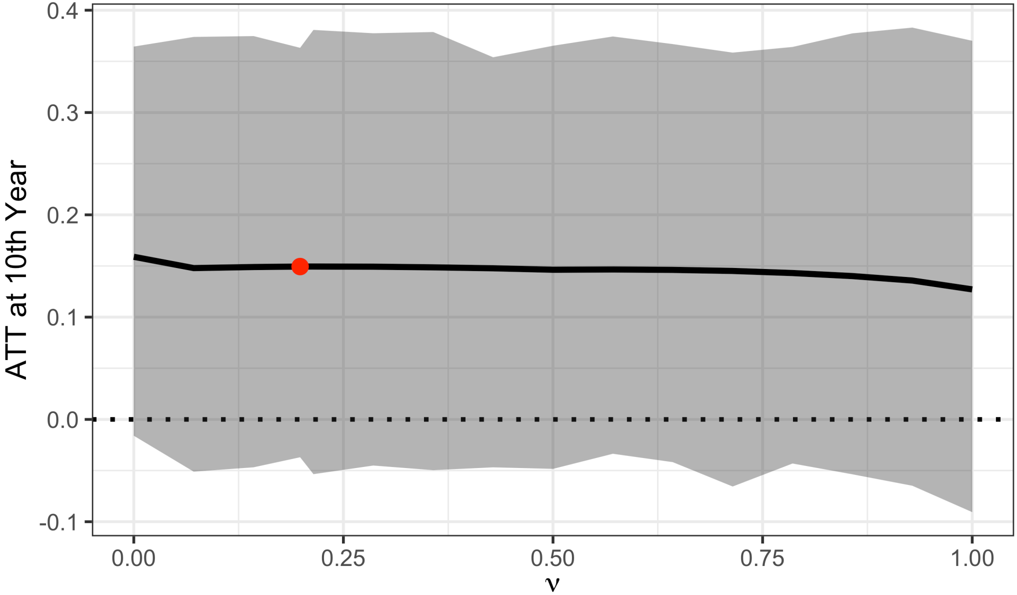
In-time placebo (2 years)



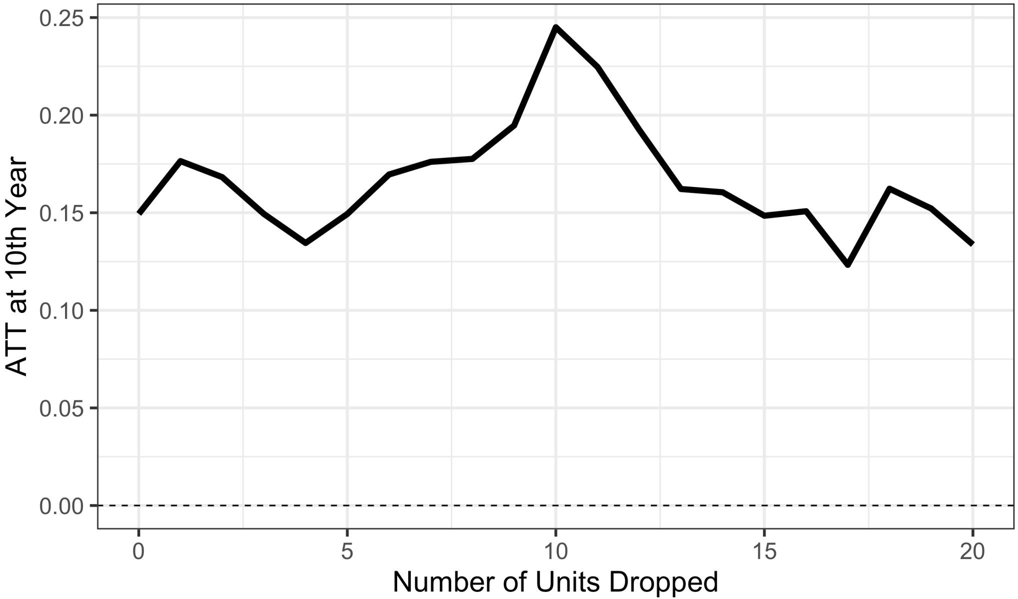
In-time placebo (6 years)



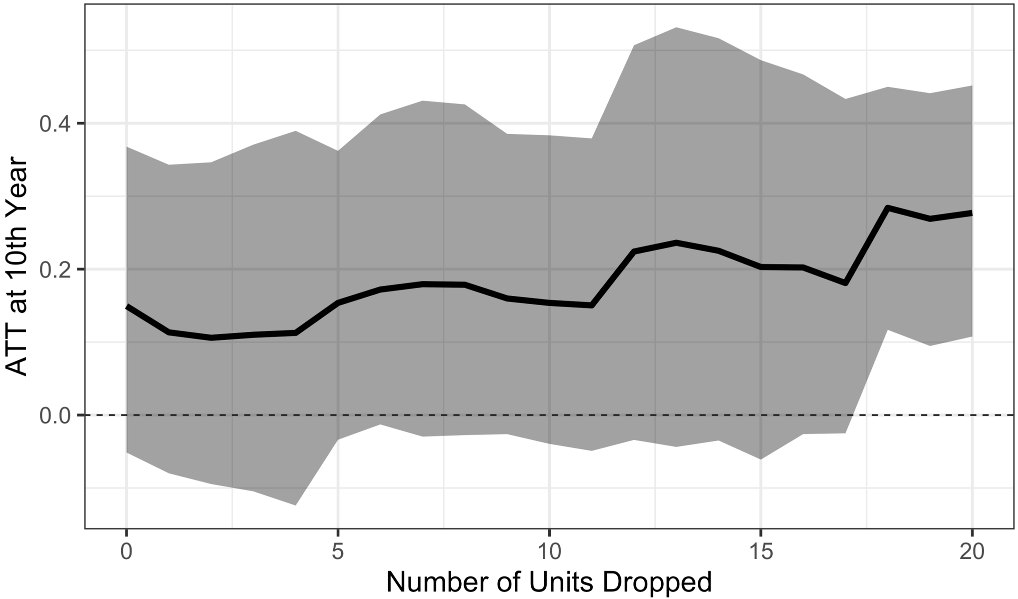
Sensitivity to choice of ν



Dropping worst-fit units: P. Pooled SCM



Dropping worst-fit units: P. Pooled SCM + Intercept + Covariates



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