# Synthetic Controls with Staggered Adoption

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



Year of Right to Carry

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Year of Right to Carry



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- "More guns, less crime"? [Lott and Mustard, 1997]
- New research says no [Donohue et al., 2019]



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- Synthetic Control Method (SCM) designed for single treated unit

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- Synthetic Control Method (SCM) designed for single treated unit

Partially pooled SCM

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

#### What do we want to estimate?

Units: i = 1, ..., N, J total treated units

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

Outcome: at event time k,  $Y_{i,T_i+k}$ 

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

$$\text{treat} = \left(\begin{array}{ccc} \checkmark & \checkmark & \checkmark \\ & \checkmark & \checkmark \\ & & \checkmark \\ & & \checkmark \end{array}\right)$$

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Basic building block:

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

	(	$\checkmark$	$\checkmark$	$\checkmark$	
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Basic building block:

 $\mathsf{treat} = \left(\begin{array}{ccc} \checkmark & \checkmark & \checkmark \\ & \checkmark & \checkmark \\ & & \checkmark \\ & & \checkmark \end{array}\right)$ 

Average at event time k:

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

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

# Separate Synthetic Controls











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#### Separate SCM



# Partially Pooled SCM

#### Separate SCM



#### Pooled SCM



#### Pooled SCM





#### ND

#### Pooled Balance is better!



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#### ... but State Balance is worse

#### - Bad for **state estimates**



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- When DGP varies over time



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Find weights that balance both Pooled Balance and State Balance

#### Balance possibility frontier



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#### 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]

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

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

#### Intercept-Shifted SCM

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

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

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

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

Treatment effect estimate is weighted difference-in-differences

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

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















#### Partially Pooled SCM



#### P. Pooled SCM w/Intercept



#### 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





#### Intercept shift + covariates



#### Recap

This paper: Extend SCM to staggered adoption

- Find weights that control State Balance and Pooled Balance
- Include an intercept to adjust for level differences
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Thank you! https://arxiv.org/abs/1912.03290 https://github.com/ebenmichael/augsynth



## Appendix

#### The role of State Balance and Pooled Balance

Generalization of parallel trends: Linear Factor Model

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

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Generalization of parallel trends: Linear Factor Model

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# Error for ATT $\left|\widehat{\mathsf{ATT}}_{0} - \mathsf{ATT}_{0}\right| \leq \|\overline{\mu}\|_{2}\|\mathsf{Pooled Balance}\|_{2} + S\sqrt{\sum_{j=1}^{J}\left\|\mathsf{State Balance}_{j}\right\|_{2}^{2}} + \sqrt{\frac{\log NJ}{T}}$

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



#### In-time placebo (2 years)



#### In-time placebo (6 years)



#### Sensitivity to choice of $\boldsymbol{\nu}$



#### Dropping worst-fit units: P. Pooled SCM


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



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