Methodological Considerations for Estimating Policy Effects in the Context of Co-occurring Policies

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Overview

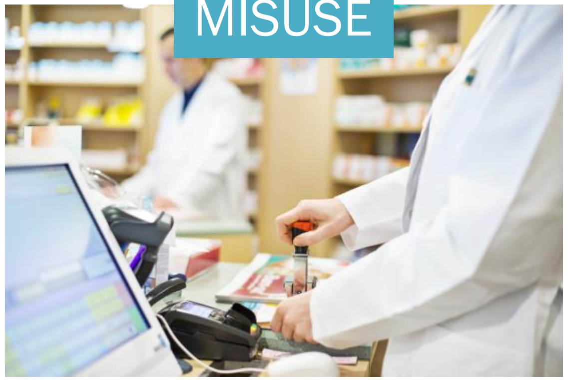
- Policy evaluation is hard, especially in the presence of co-occuring policies
- No clear understanding of which methods are optimal for disentangling the policy effects
- Simulations provide a meaningful way to identify the most promising methods
- Findings from the opioid policy space can provide some needed guidance for best practices

There are a myriad of policy approaches being tried to address the opioid crisis

INITIATION

- Day supply limits
- Unused Rx disposal
- Physician education
- Clinical guidelines
- Insurance coverage for non-opioid pain management options

MISUSE



- PDMPs
- Drug reformulation
- Pain clinic regulations
- High dose limits
- Insurance pre-authorization

TREATMENT & RECOVERY

- Expanded MOUD coverage
- Mandated SUD benefit coverage
- Physician waivers patient limits raised
- Low barrier MOUD access

HARM REDUCTION

- Naloxone access laws
- Naloxone distribution campaigns
- Good Samaritan laws
- Fentanyl test strips

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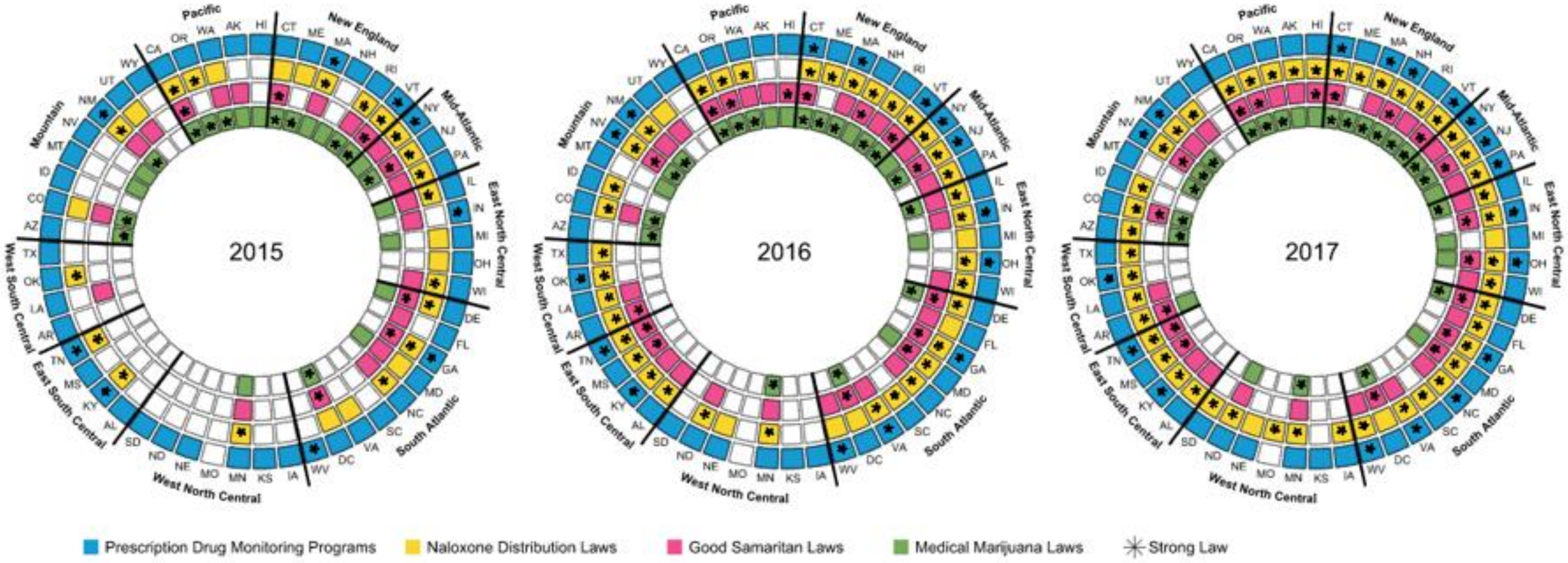
Disentangling effects of co-occurring policies

- We know states are not enacting policies in a vacuum
- Prior work identified correlation in types of policies adopted in various places



Current practice for handling co-occurring policies

- In evaluation studies, there is typically one “primary” policy of interest
  - Goal: isolate impact of this policy from that of any co-occurring policies
- Ignoring co-occurring policies in analyses will result in model misspecification
  - Potentially biases effect estimate for the primary policy
- In our opioid policy literature review of publications between 2005 to 2018:
  - 66% did not address any co-occurring policies in the analytic design
  - 8% adjusted for a single co-occurring policy in the primary analyses
  - 20% accounted for 2+ co-occurring policies in the primary analyses
  - 5% accounted for co-occurring policies in a secondary or sensitivity analyses

Various potential solutions but no clear understanding of how these approaches perform

- In practice, need to think critically & be transparent about policies that co-occur with (and may confound) the primary policy of interest
- Commonly used analytic approaches:
  - Co-occurring policies are controlled for as regression covariates
  - Studies restrict sample or study period – for example:
    - Restrict to subset of states that do not have any additional opioid policies during the study period
    - Define study period to end prior to adoption of potential confounding policy
- Additionally, co-occurring policies may yield synergistic policy effects and yet additive or interactive effects rarely examined

Our objective: To examine the performance of different statistical models when we have co-occurring policies enacted using simulations

Our simulation had 3 key phases

Simulate enactment of co-occurring policies and their effects in real data

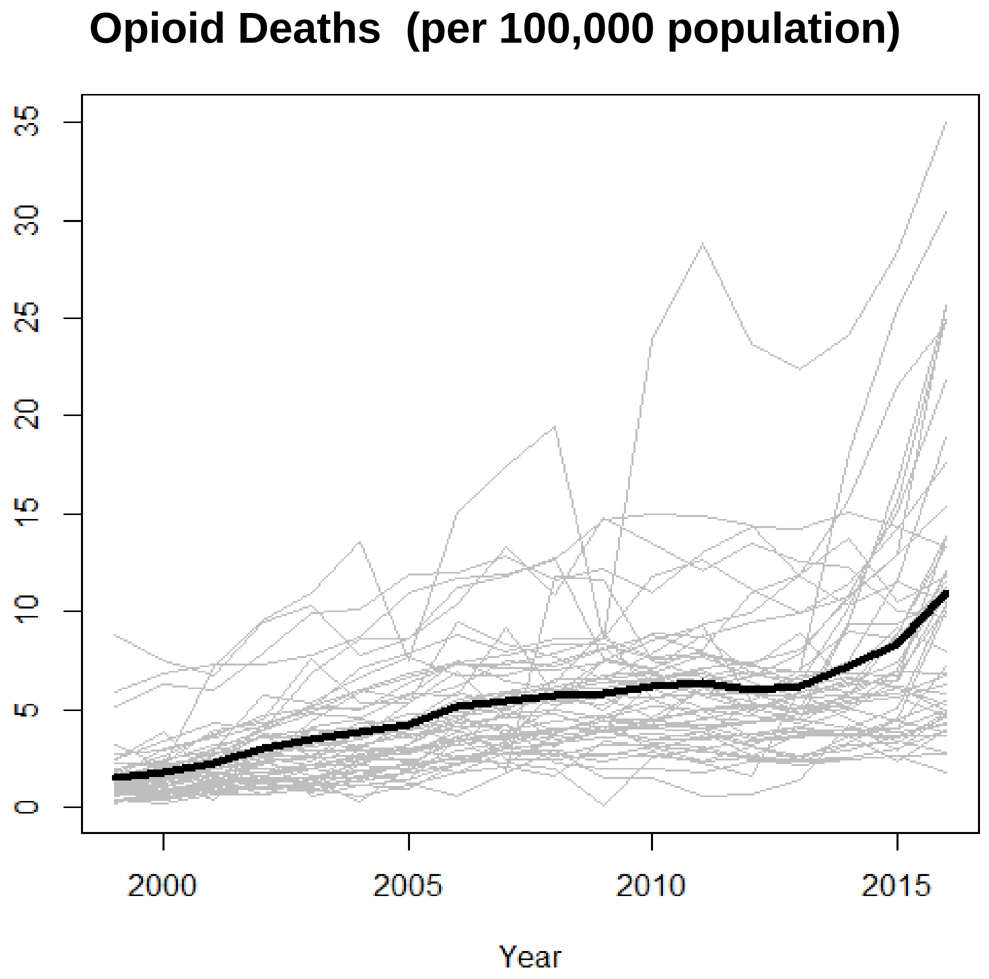
Estimate policy effects using statistical models

Compare model performance

Co-occurring policies: Illustration of how we simulate policy effects

Simulate | Estimate | Compare

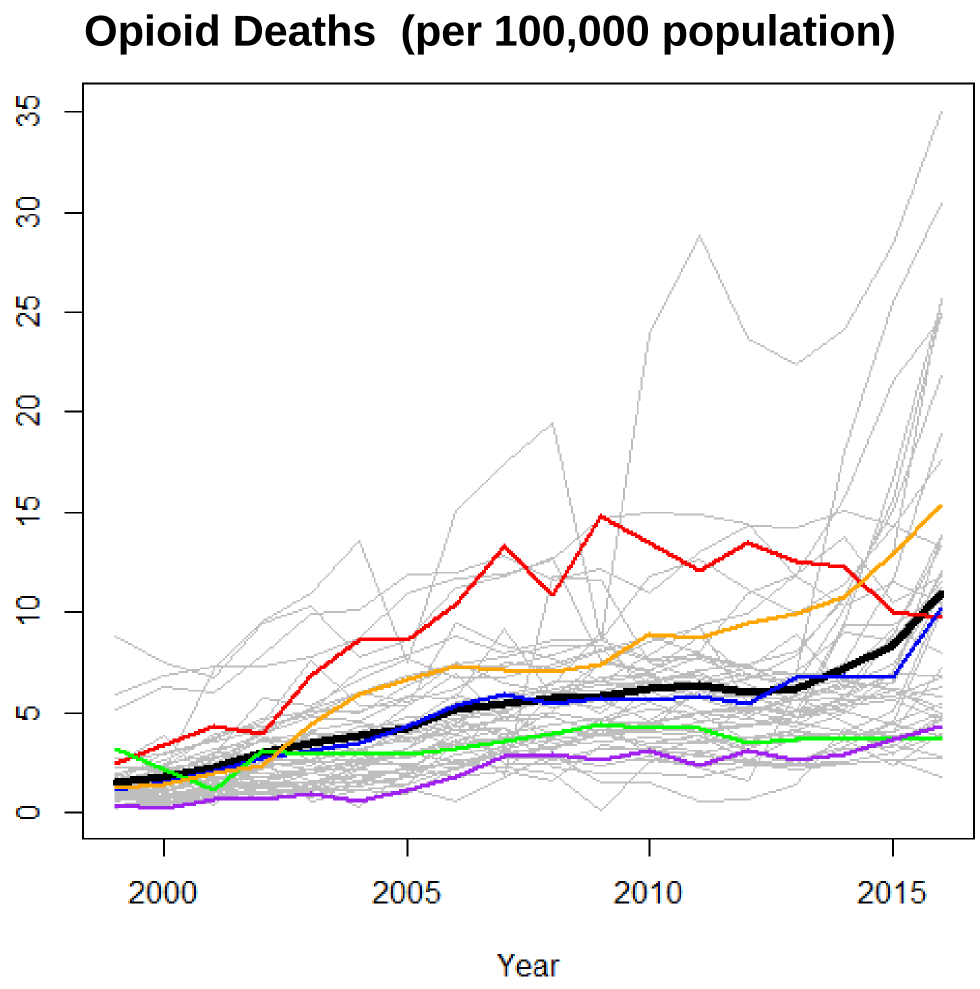
1. Real U.S. state opioid-related death rates



Co-occurring policies: Illustration of how we simulate policy effects

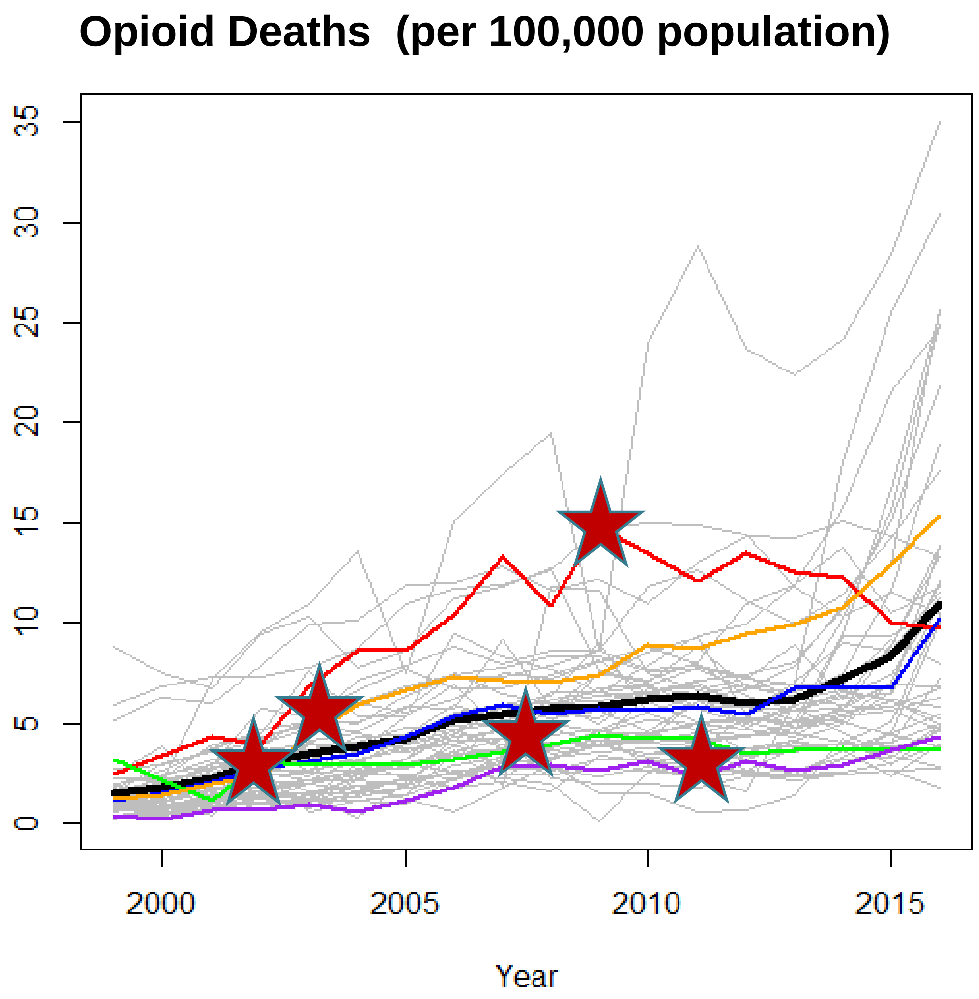
Simulate | Estimate | Compare

1. Real U.S. state opioid-related death rates
2. Randomly select 5 states



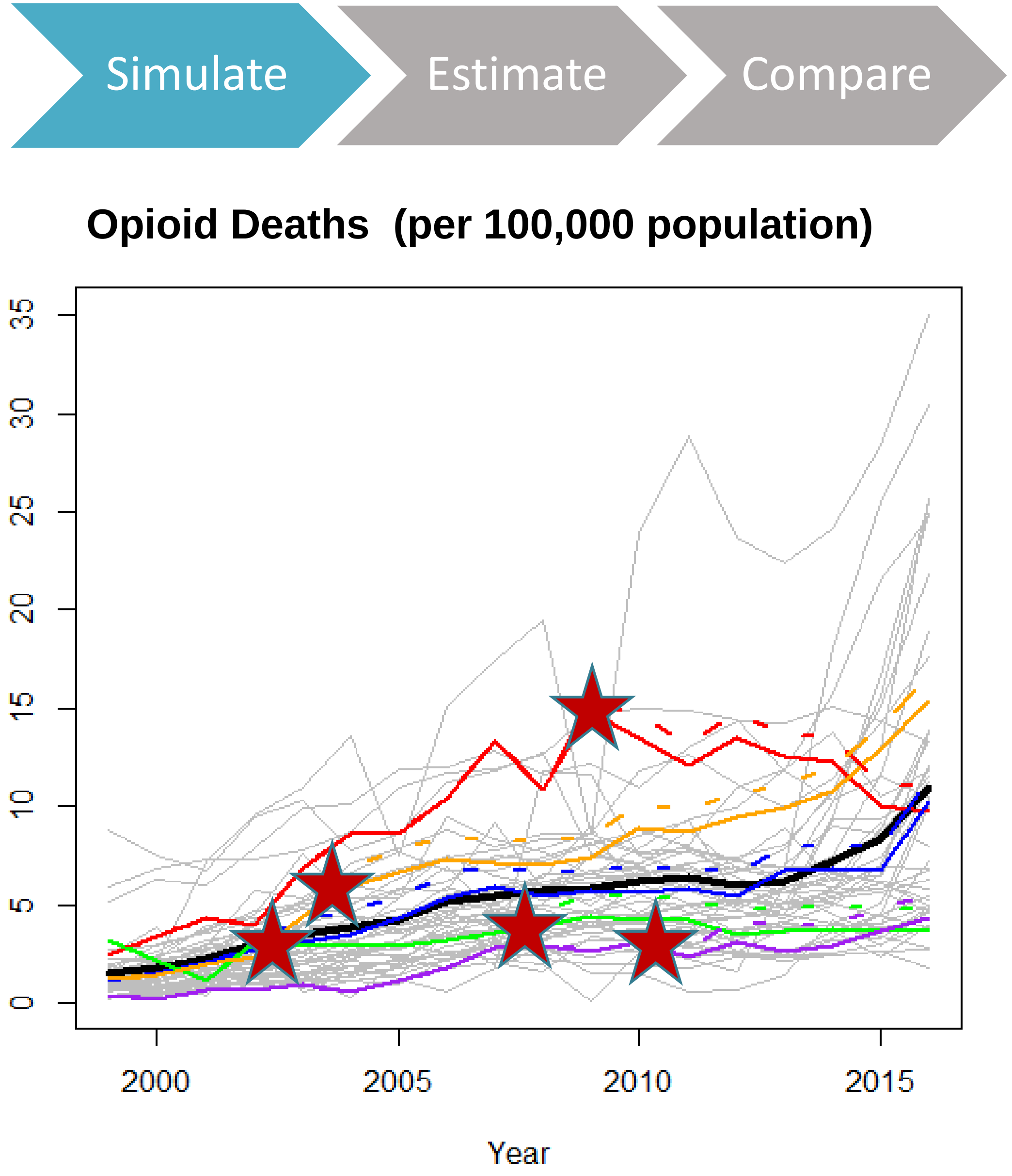
Co-occurring policies: Illustration of how we simulate policy effects

1. Real U.S. state opioid-related death rates
2. Randomly select 5 states
3. Randomly select enactment date for first policy



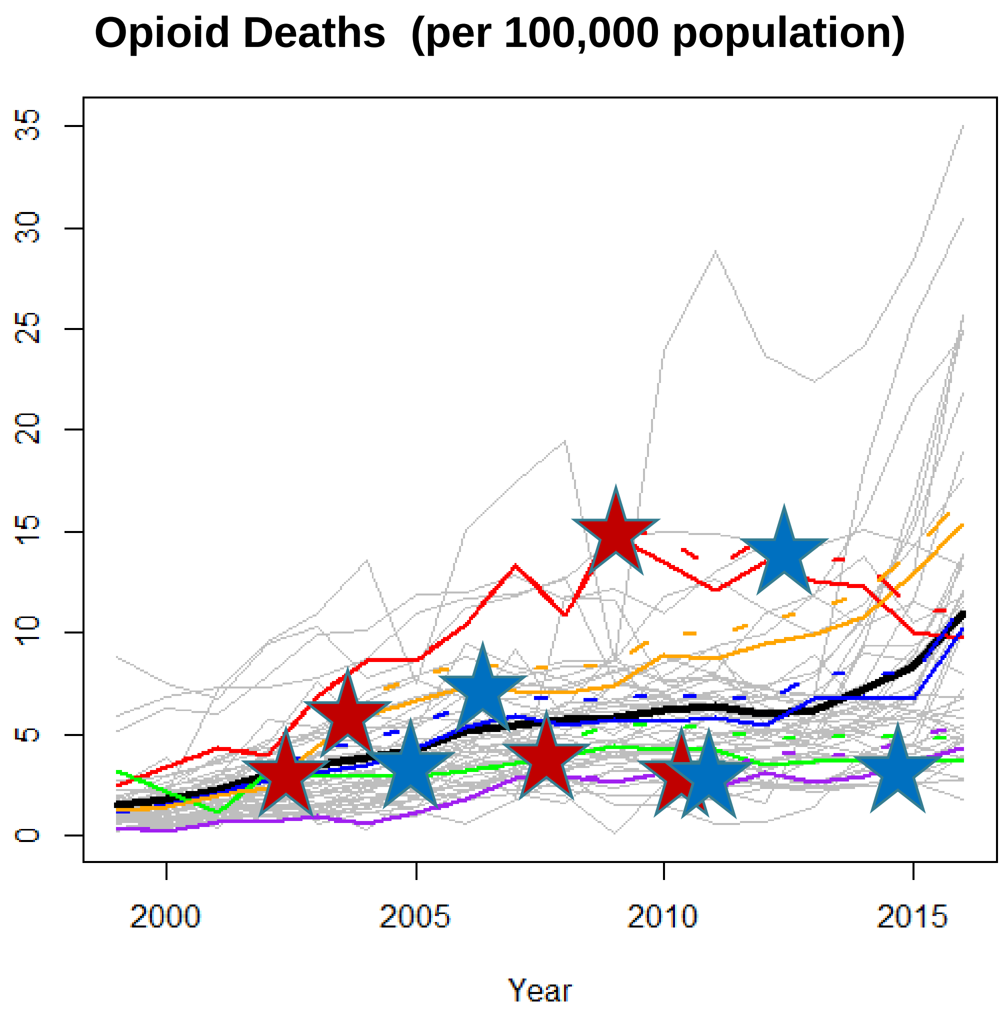
Co-occurring policies: Illustration of how we simulate policy effects

1. Real U.S. state opioid-related death rates
2. Randomly select 5 states
3. Randomly select enactment date for first policy
4. Generate data with policy effect after enactment date



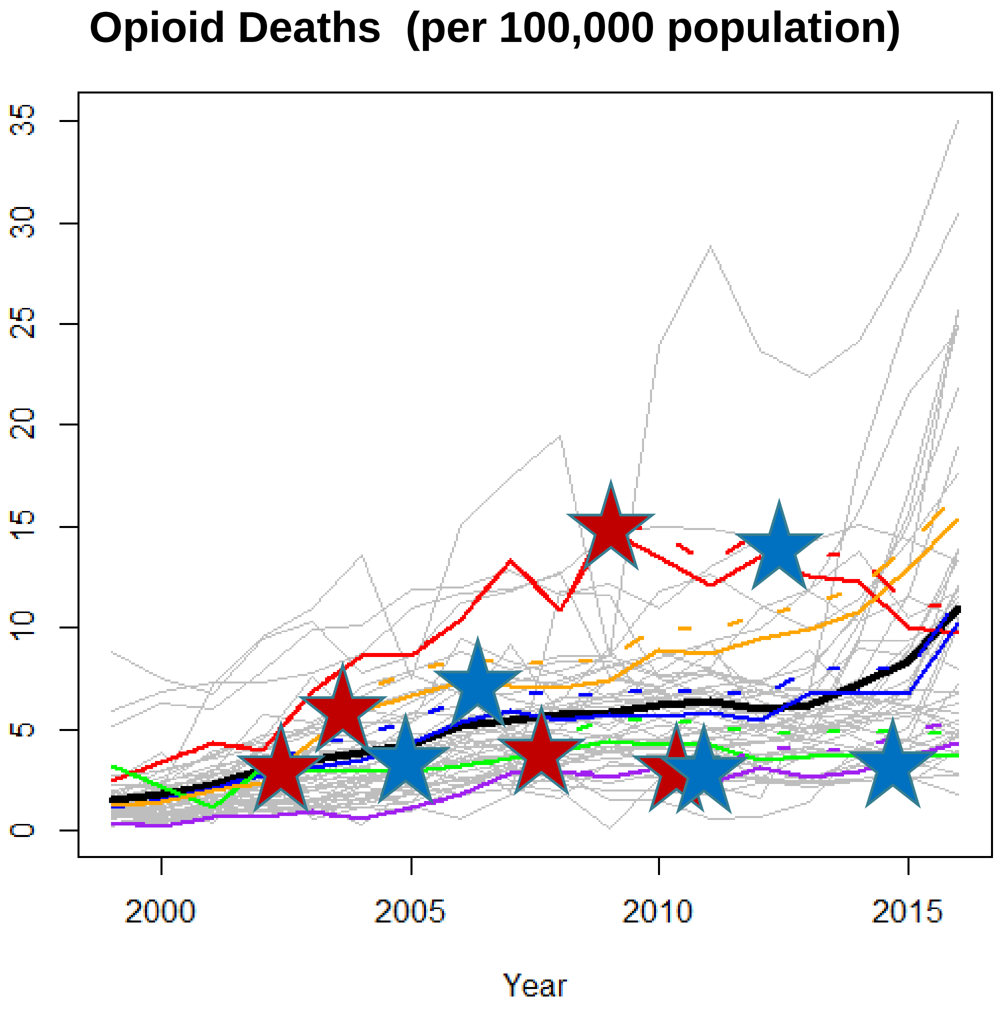
Co-occurring policies: Illustration of how we simulate policy effects

1. Real U.S. state opioid-related death rates
2. Randomly select 5 states
3. Randomly select enactment date for first policy
4. Generate data with policy effect after enactment date
5. Select enactment date for next policy to be a fixed number of years later



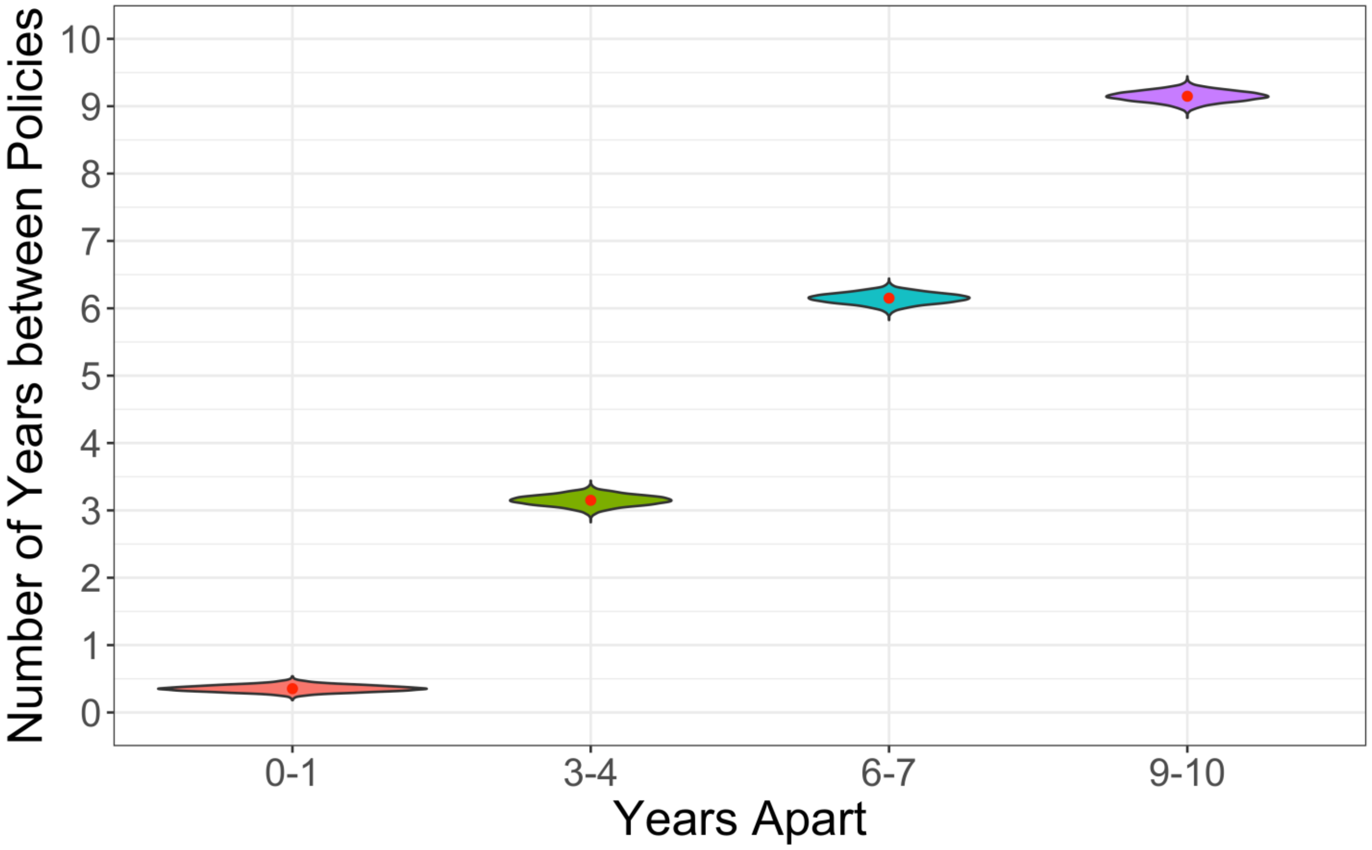
Co-occurring policies: Illustration of how we simulate policy effects

1. Real U.S. state opioid-related death rates
2. Randomly select 5 states
3. Randomly select enactment date for first policy
4. Generate data with policy effect after enactment date
5. Select enactment date for next policy to be a fixed number of years later
6. Insert policy effect of 2nd co-occuring policies



Simulation design allows us to examine several different core factors that will impact performance

1. Randomly sample a set of states that will enact both policies (n.trt = 5 and 30)
2. Randomly select 2 enactment dates assuming a fixed average length of time between them (yrs.apart = 0, 3, 6, 9 years)
3. Consider cases where policies occurred in fixed order (primary always first) versus random order
4. Assume policies have an additive effect on the outcome ($Y_{it}^{*} = Y_{it} + \gamma_1 * A_{1it} + \gamma_2 * A_{2it}$)



Statistical models considered

Simulate | Estimate | Compare

Correctly specified models: Control for indicators of both policies (A_{1it}, A_{2it})

Classic two-way fixed effects model (Difference-in-differences [DID]):

$$Y_{it}^{*} = \alpha_1 \cdot A_{1it} + \alpha_2 \cdot A_{2it} + \beta \cdot X_{it} + \rho_i + \sigma_t + \epsilon_{it}$$

Versus the autoregressive (AR) model:

$$Y_{it}^{*} = \alpha_1 \cdot (A_{1it} - A_{1i,t-1}) + \alpha_2 \cdot (A_{2it} - A_{2i,t-1}) + \beta \cdot X_{it} + \gamma \cdot Y_{it-1}^{*} + \sigma_t + \epsilon_{it}$$

Misspecified models: Only control for one of the policies (A_{1it})

Classic two-way fixed effects model (DID):

$$Y_{it}^{*} = \alpha_1 \cdot A_{1it} + \beta \cdot X_{it} + \rho_i + \sigma_t + \epsilon_{it}$$

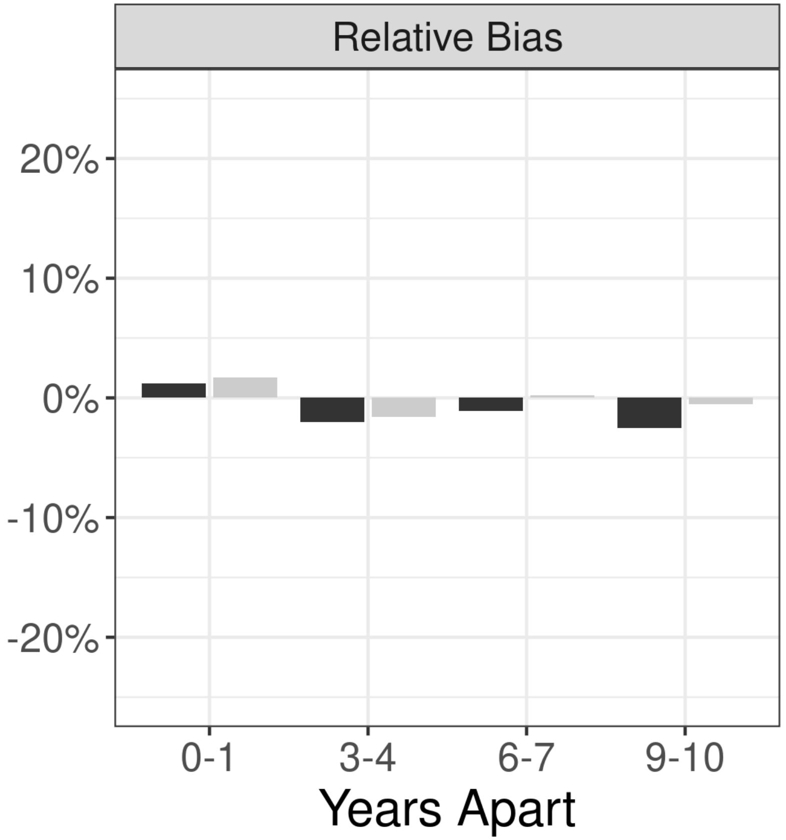
Versus the AR model:

$$Y_{it}^{*} = \alpha_1 \cdot (A_{1it} - A_{1i,t-1}) + \beta \cdot X_{it} + \gamma \cdot Y_{it-1}^{*} + \sigma_t + \epsilon_{it}$$

Findings when policies are random, effects both = -10% and we have 30 treated states

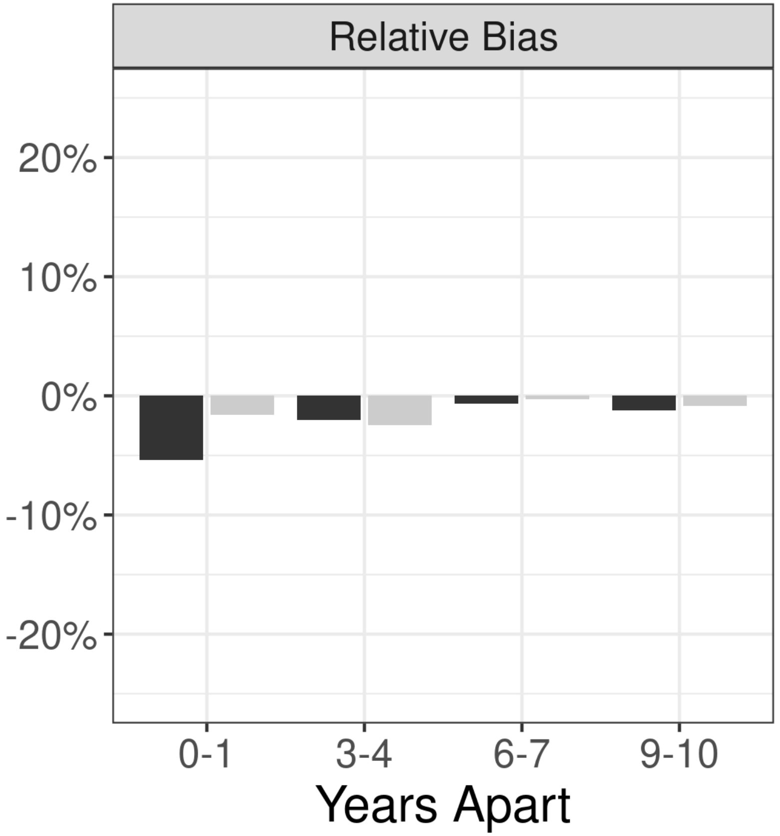
Correctly specified models: Relative bias is low and decreases as length of time between policy enactment dates increases

Autoregressive Model



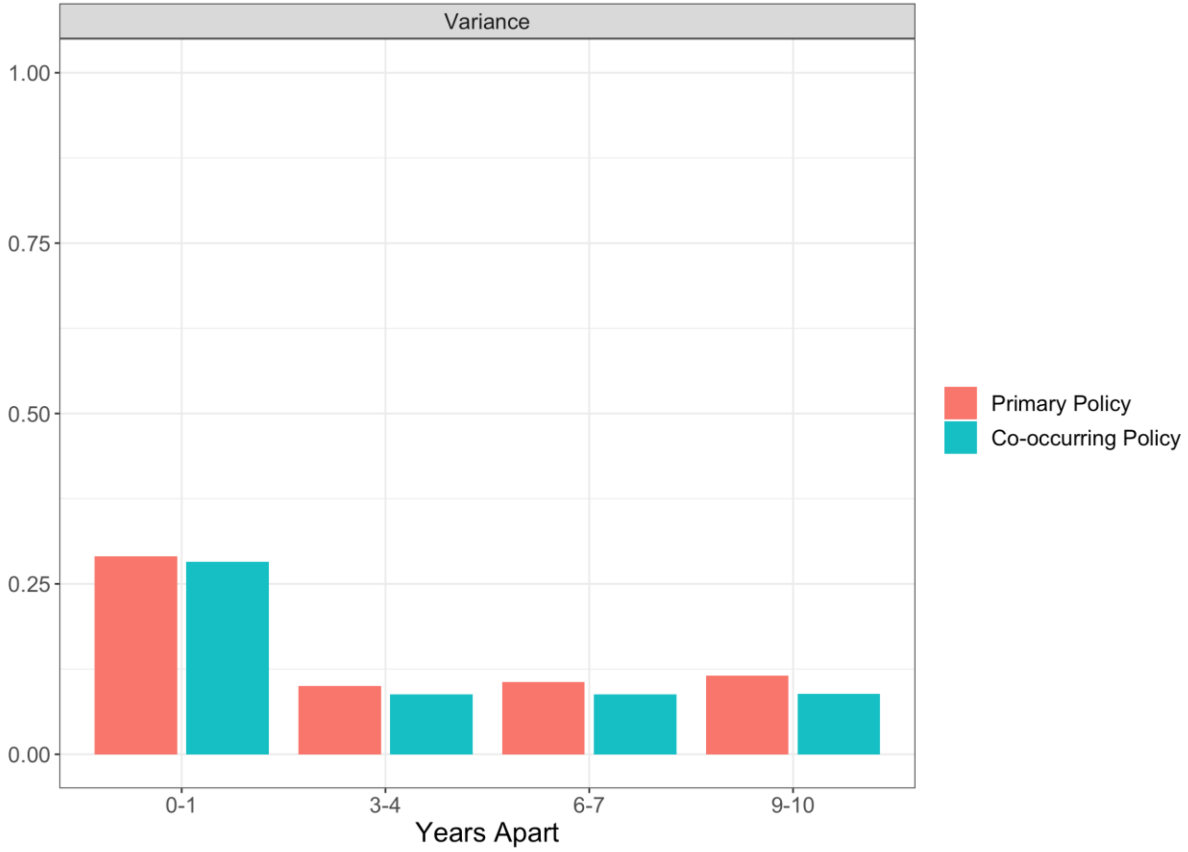
Primary Policy
Co-occurring Policy

Two-way Fixed Effects Model

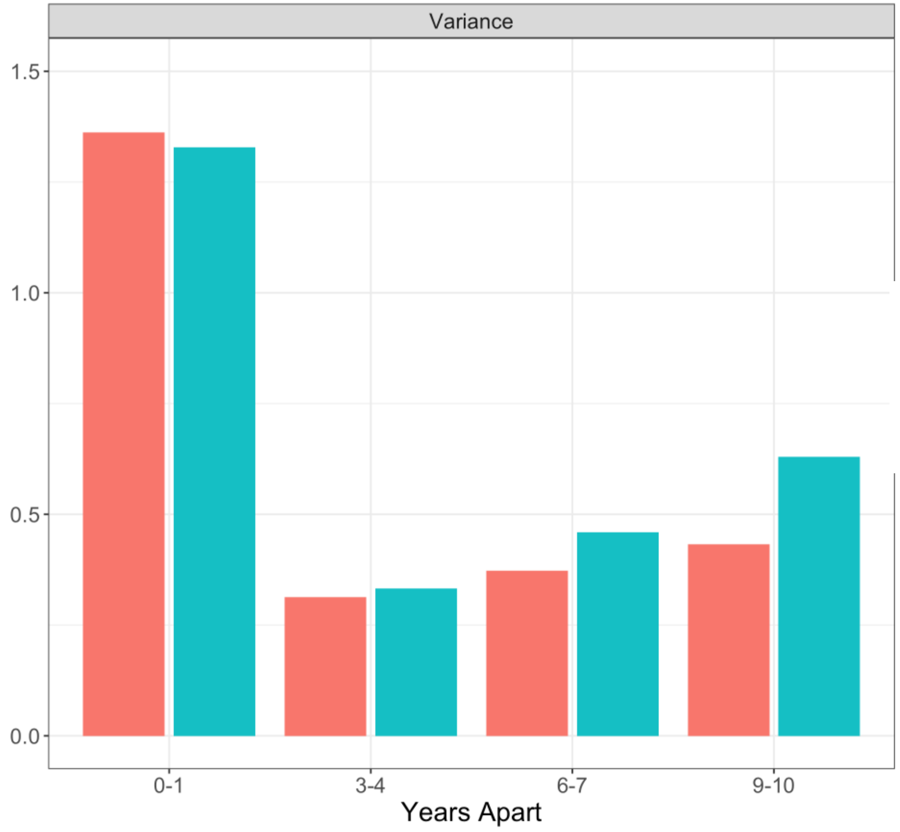


Correctly specified models: Variance greatest when policies enacted in rapid succession (0-1 years apart)

Autoregressive Model

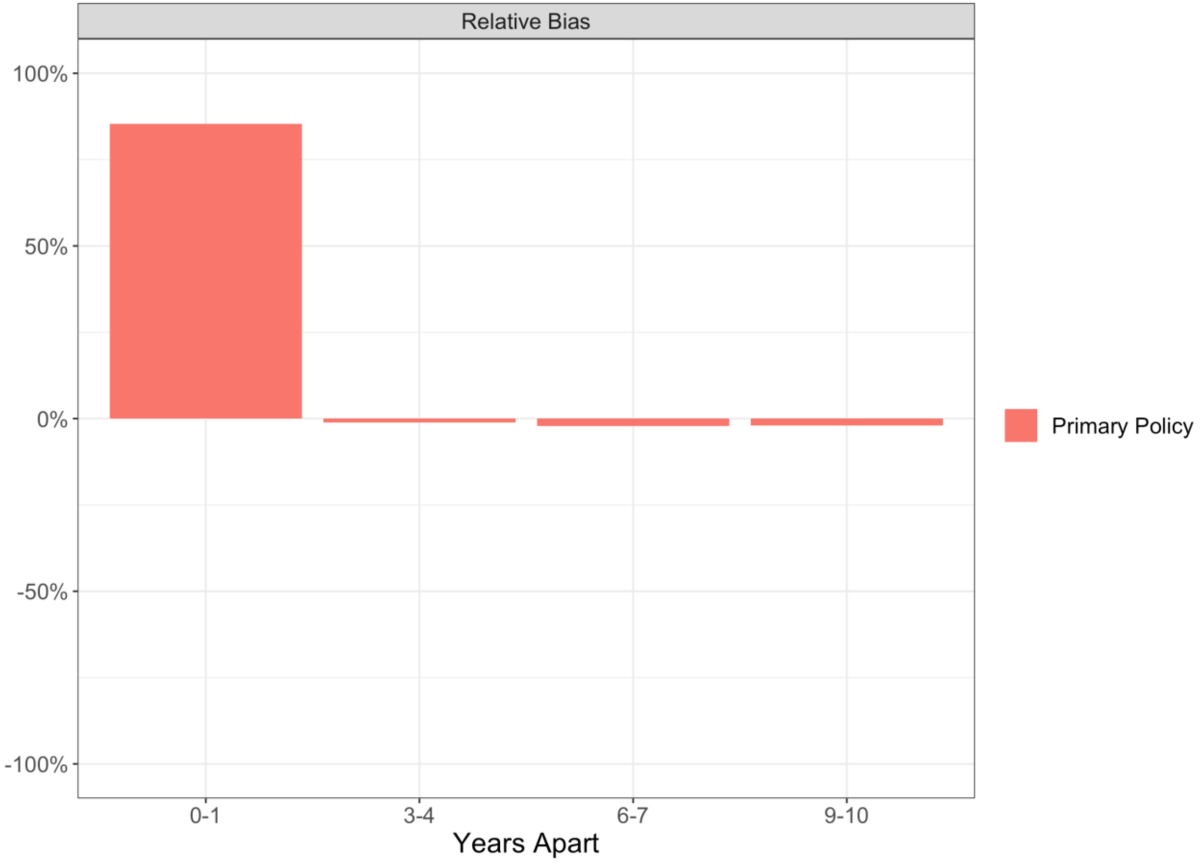


Two-way Fixed Effects Model

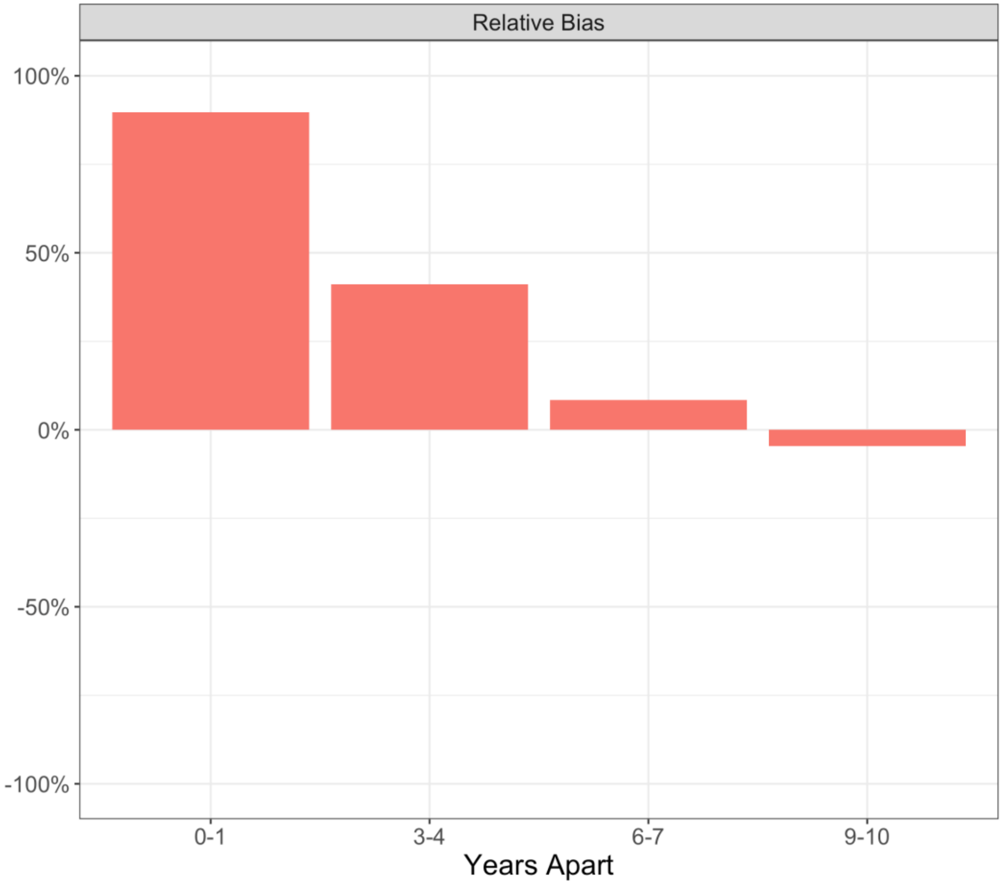


Misspecified models: Relative bias is substantially worse in the case with ~0-1 years between enactment dates

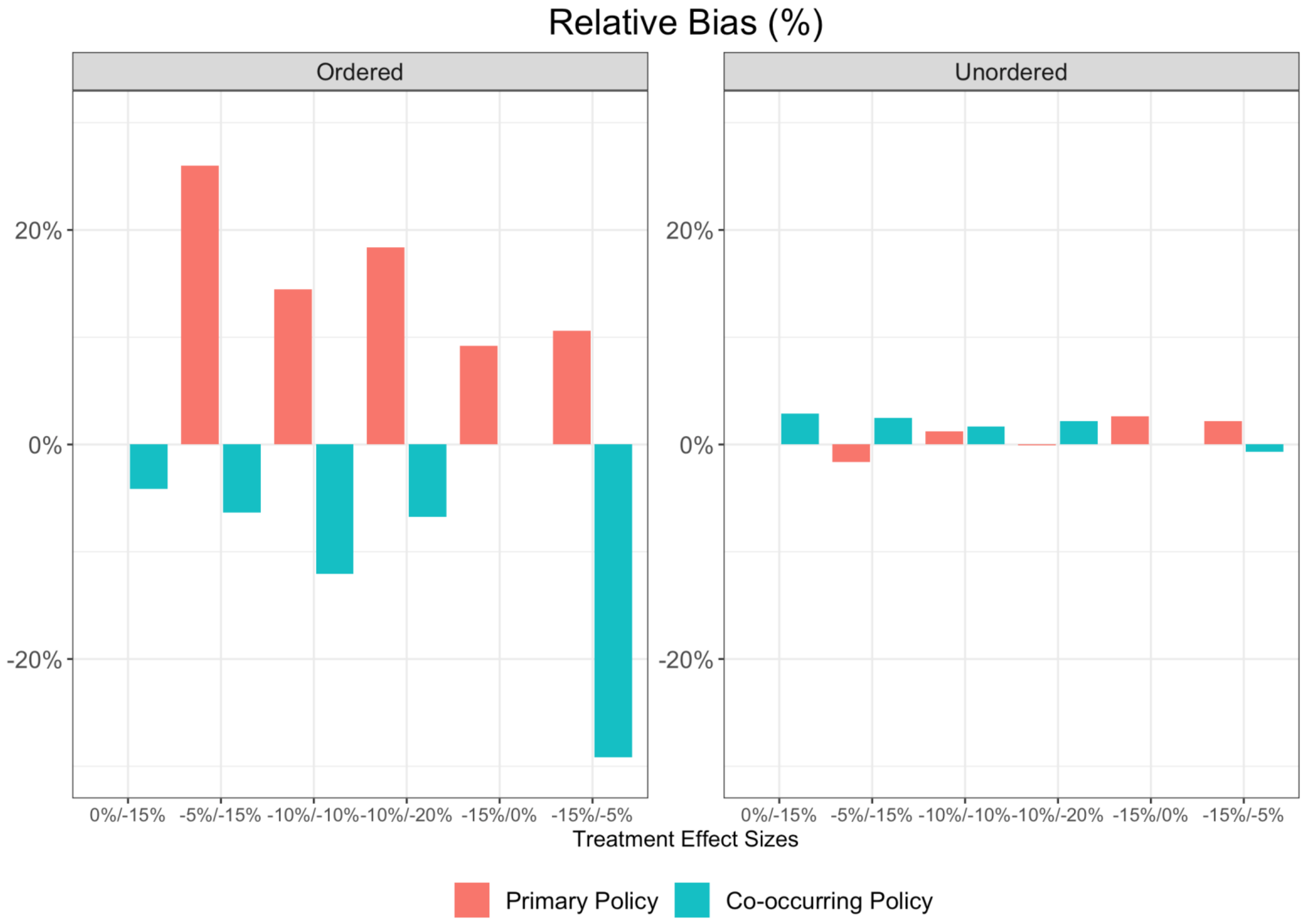
Autoregressive Model



Two-way Fixed Effects Model



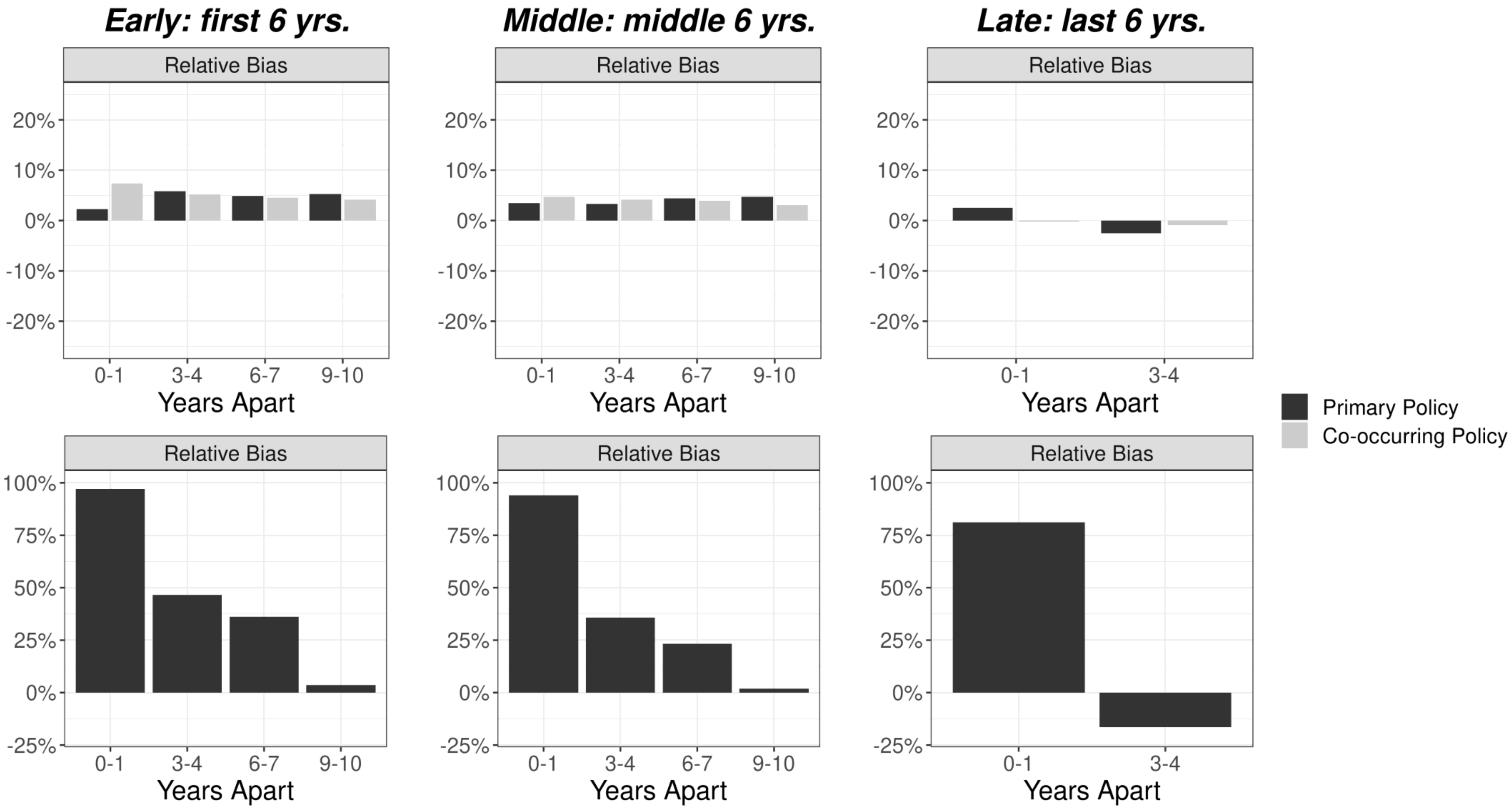
Correctly specified models do better when policies do not occur in fixed order



Bias and variance greatest when timing of the enactment for the first policy occurs earlier versus later in the time series

Correctly-specified AR model:

Misspecified AR model:



Key recommendations for practice - 1

- Estimates of policy effects should consider confounding from co-occurring policies, particularly when enacted close together (0-1 years apart)
- If the co-occurring policy is a confounder, leaving it out will introduce ***unobserved confounding bias*** in the estimate of the primary policy
  - Bias ~ 75% if policies enacted in rapid succession (0-1 years apart)
  - Less of a problem as length of time between enactment dates gets larger
- Optimal model controls for both confounders
  - Performance better when policies not ordered
  - Variance stabilizes for AR model once policies >3-4 years apart and for classic DID >6-7 years apart

Key recommendations for practice - 2

Propose the use of simple data checks prior to policy evaluations

- Compute length of time between enactment dates for each state
- Examine distribution to ensure there is enough time between enactment dates
  - With AR models – need > 3 years to eliminate bias and optimize precision
  - With classic DID – need > 6 years to eliminate bias and optimize precision

◇ Griffin, B.A., Schuler, M, Pane, J., Grimm, G., Patrick, S., Stein, B.D., Smart, R., Stuart, E.A,. Methodological considerations for estimating policy effects in the context of co-occurring policies. Health Serv Outcomes Res Method. 2023, 23(2):149-165. doi: 10.1007/s10742-022-00284-w.

Final notes

- Key limitations of current work: Still haven't studied model performance when we have interaction effects between the co-occurring policies

- R package (optic) available and easy to use to implement our simulations with any type of repeated measures data

optic 1.0.0

optic

Simulation Tool for Causal Inference Using Longitudinal Data

R-CMD-check passing test-coverage passing

The `optic` R package helps you scrutinize candidate causal inference models using **your own** longitudinal data. Researchers from the Opioid Policy Tools and Information Center (OPTIC) initially created the tool to examine longitudinal data related to opioids, but its framework can be used with longitudinal data on topics other than opioids.

Background and Rationale

Recent difference-in-differences (DID) literature revealed issues with the traditional DID model, but we found it very difficult to evaluate the relative performance of different causal inference methods using our own data. Thus, we designed a series of simulations (Griffin et al. 2021; Griffin et al. 2023) to study the performance of various methods under different scenarios. Our publications to date are as follows:

1. In Griffin et al. (2021), we use real-world data on opioid mortality rates to assess commonly used

Thank you!!

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