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

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Joint work with Avi Feller and Elizabeth Stuart

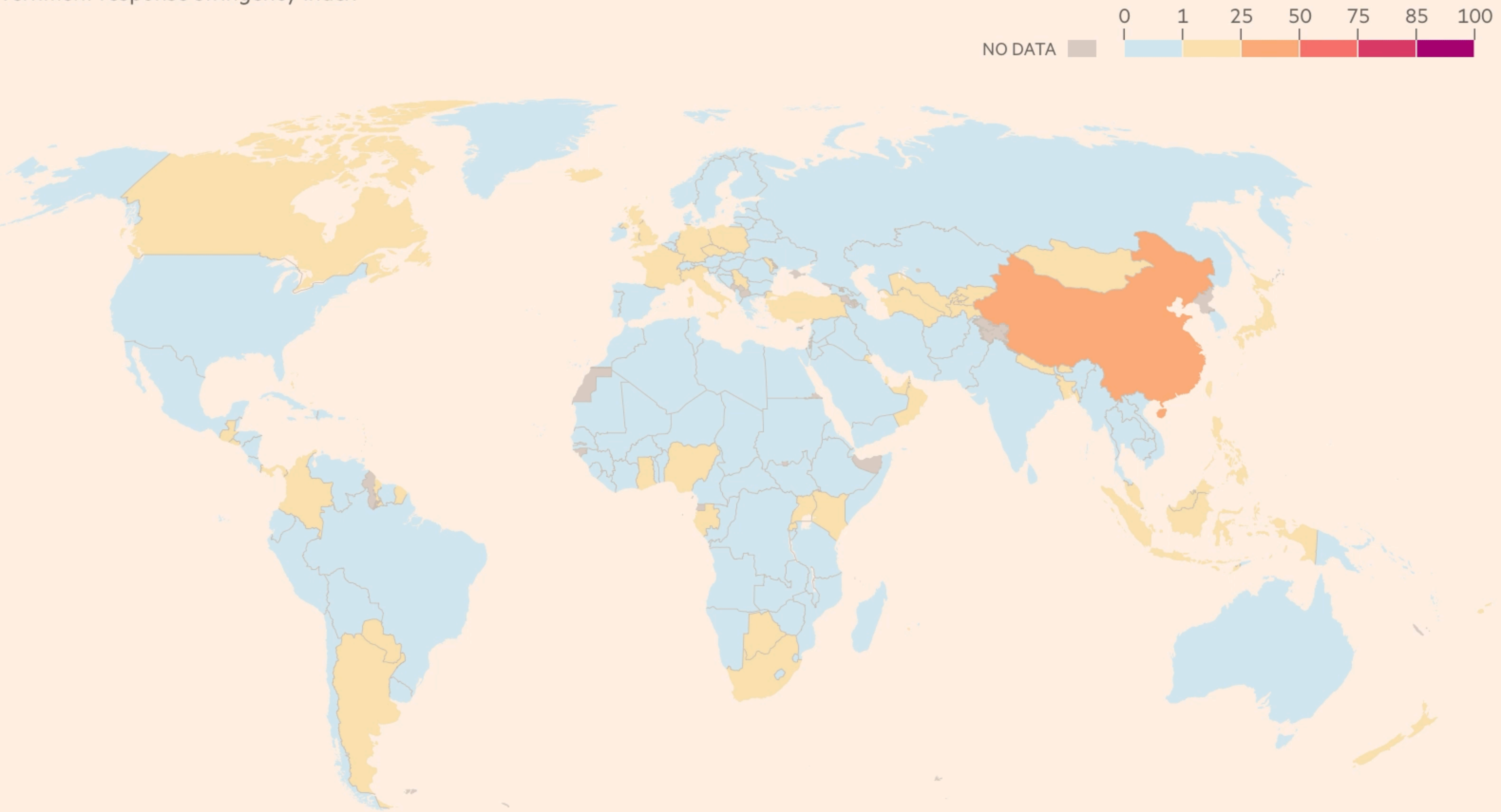
2020 was an extraordinary year (for policy evaluation)

- Unprecedented policy measures
- Wide variation in types of NPIs
- Rapidly changing policy environment

Jan 24 2020

Lockdowns around the world

Oxford Covid-19 government response stringency index



Graphic: Alan Smith and David Blood

Source: Blavatnik School of Government, University of Oxford. Data as of April 22. Data for the most recent seven days may not yet reflect government response changes implemented during that period

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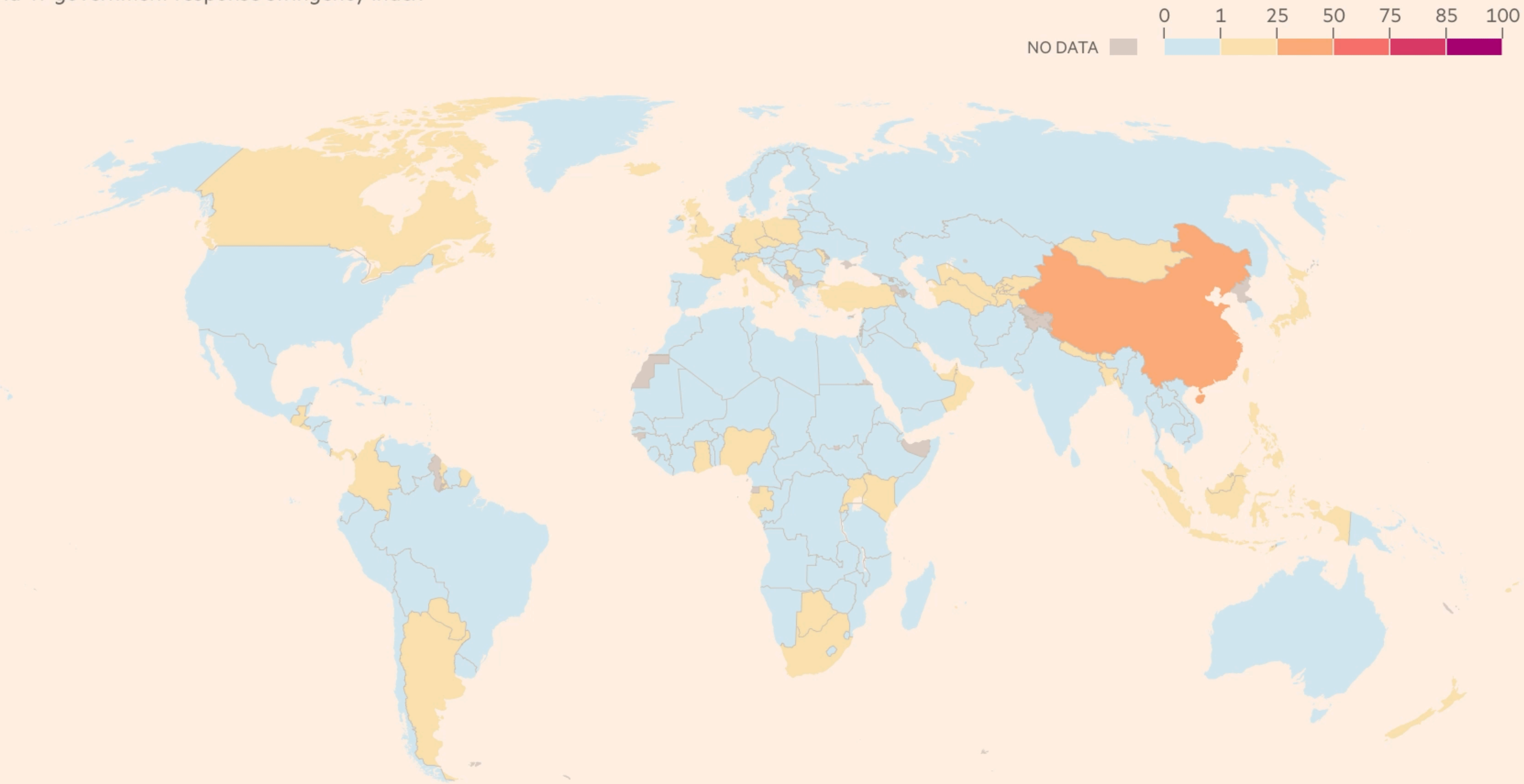

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Policy evaluation is hard!

…especially during Covid-19

What's so difficult?

(an incomplete list)

- Policies are not randomized
- Policies are adopted at different times
- Multiple policies are bundled together
- Policies do not determine individual behavior
- Policies in one location might affect another

But it's important to evaluate policy impacts!

Design-based thinking can help

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Target Trial Emulation

Design an observational study like a randomized one

[Danaei et al 2018; Dickerman et al 2019]

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Panel Data Methods

Beyond two-way fixed effects

[Goodman-Bacon 2018; Abraham & Sun 2021; Callaway & Sant'Anna 2021]

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Combines insights from Epidemiology and Econometrics

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Policy Trial Emulation

Combines insights from Epidemiology and Econometrics

A stylized analysis:

- Evaluate the impact of stay at home orders in the US

Outline

1. The elements of policy trial emulation
2. Single and nested target trials

Policy Trial Emulation

The elements of policy trial emulation

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Require 4 definitions:

The elements of policy trial emulation

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1. Units and exposures

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The elements of policy trial emulation

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- What is a stay-at-home policy?
  - Variation across states
  - We'll package these all together → less interpretable

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- Are we interested in policies or behavior?
  - Individual mobility reduced **before** policy changes
  - Limited compliance and enforcement

[Goolsbee & Syverson 2020]

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[Goolsbee & Syverson 2020]

- Are there spillovers?
  - Probably! But this is difficult to account for

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- Intent-to-treat (ITT) analysis
  - Measure the effect of the policy as implemented

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- Intent-to-treat (ITT) analysis
  - Measure the effect of the policy as implemented
- Potential outcomes framework
  - W_{it} State i has a stay-at-home order at time t
  - $Y_{it}(1), Y_{it}(0)$ Outcome if order is/isn't enacted
  - Average of instantaneous effects $Y_{it}(1) - Y_{it}(0)$ for states that enacted a stay at home policy

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- Only focus on starting stay-at-home orders
  - Effect of "turning off" policies adds complexity

The elements of policy trial emulation

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- Cumulative vs instantaneous outcomes
  - Total number of Covid-19 cases
  - Ratio of current current case count to previous day

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  - Logarithm transformation due to exponential growth

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- Cumulative vs instantaneous outcomes
  - Total number of Covid-19 cases
  - Ratio of current current case count to previous day
- Transforming the outcomes
  - Logarithm transformation due to exponential growth
- Data quality is a concern
  - Differential changes in testing regimes over time?

The elements of policy trial emulation

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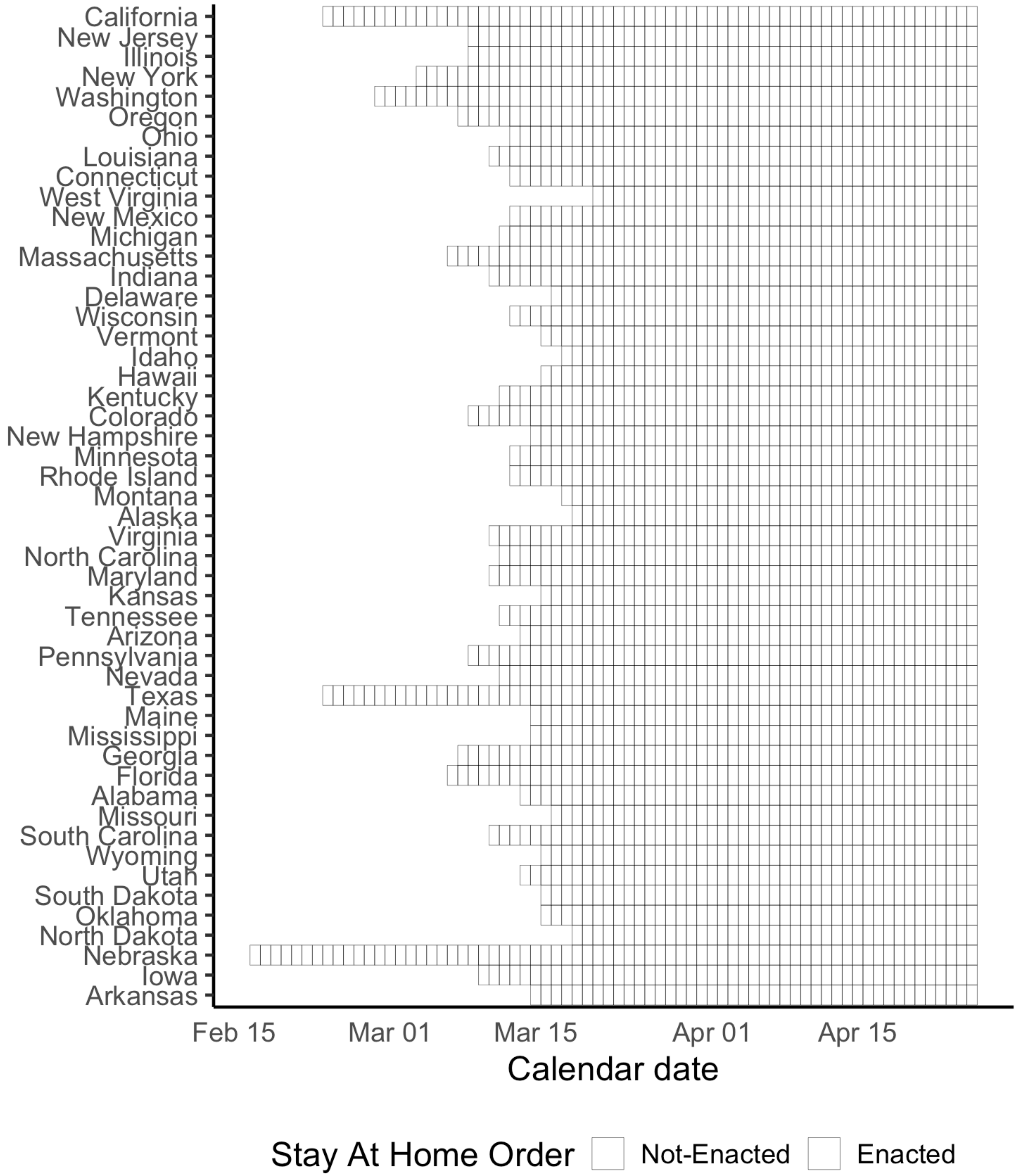
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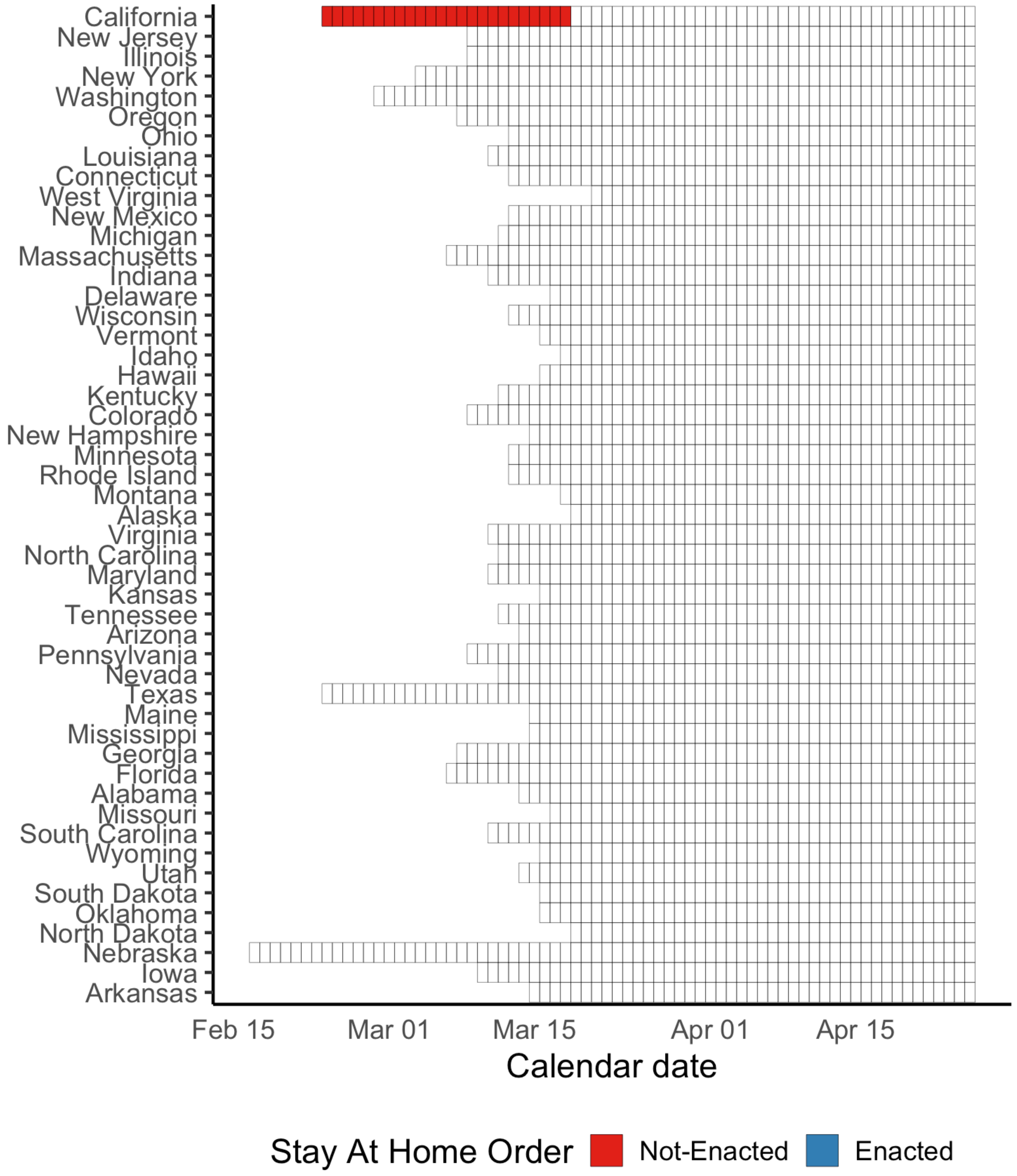
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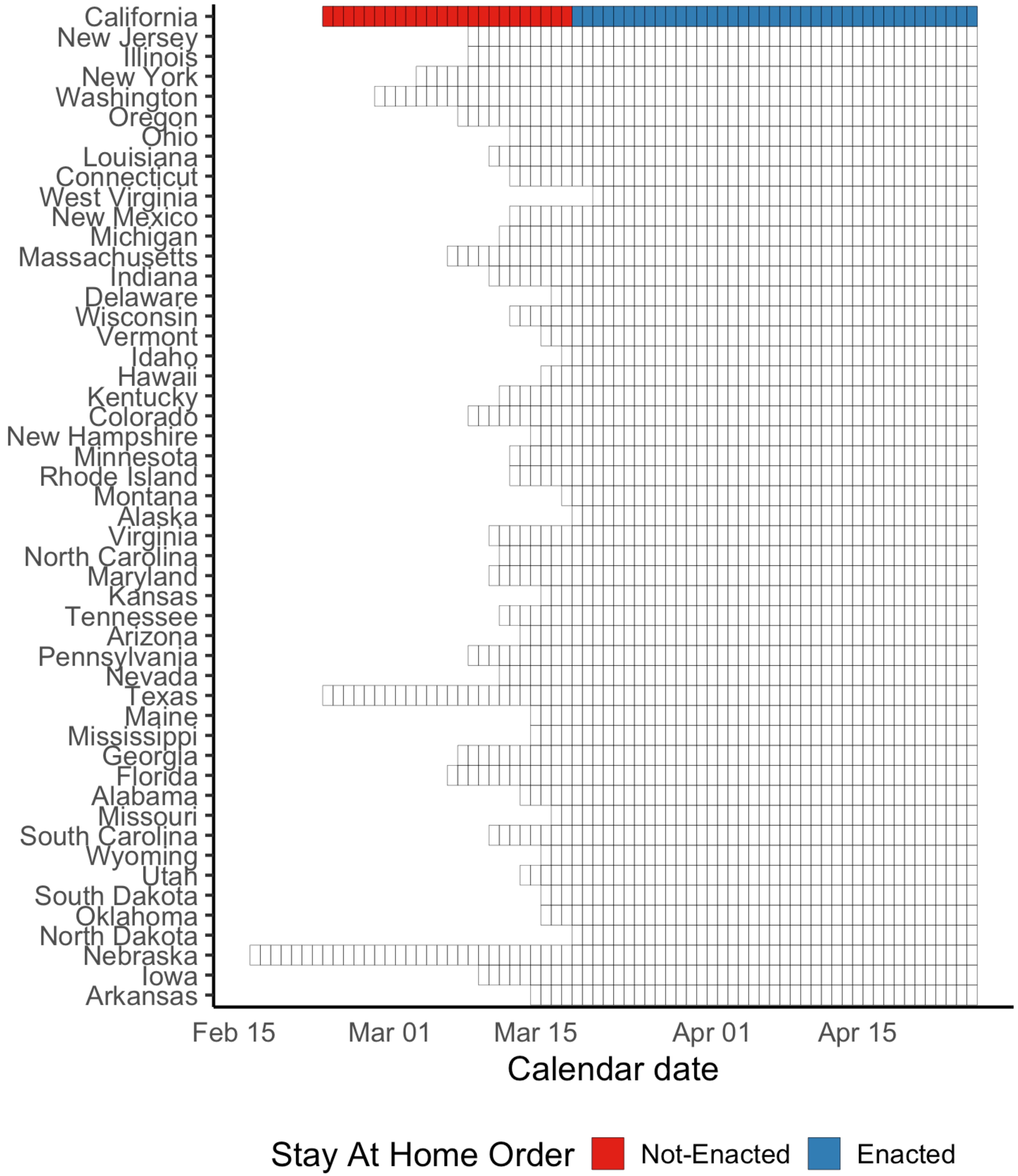
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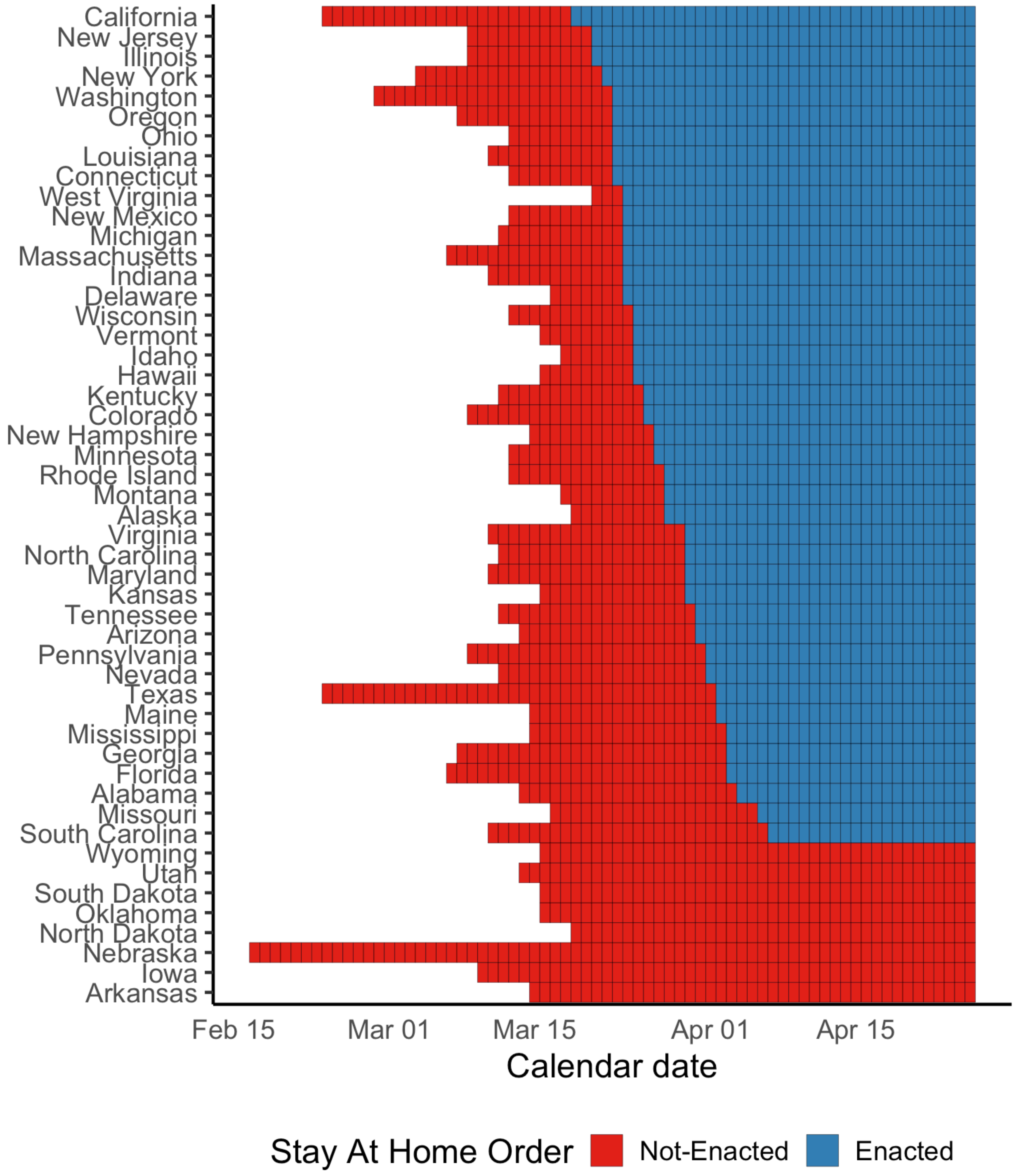
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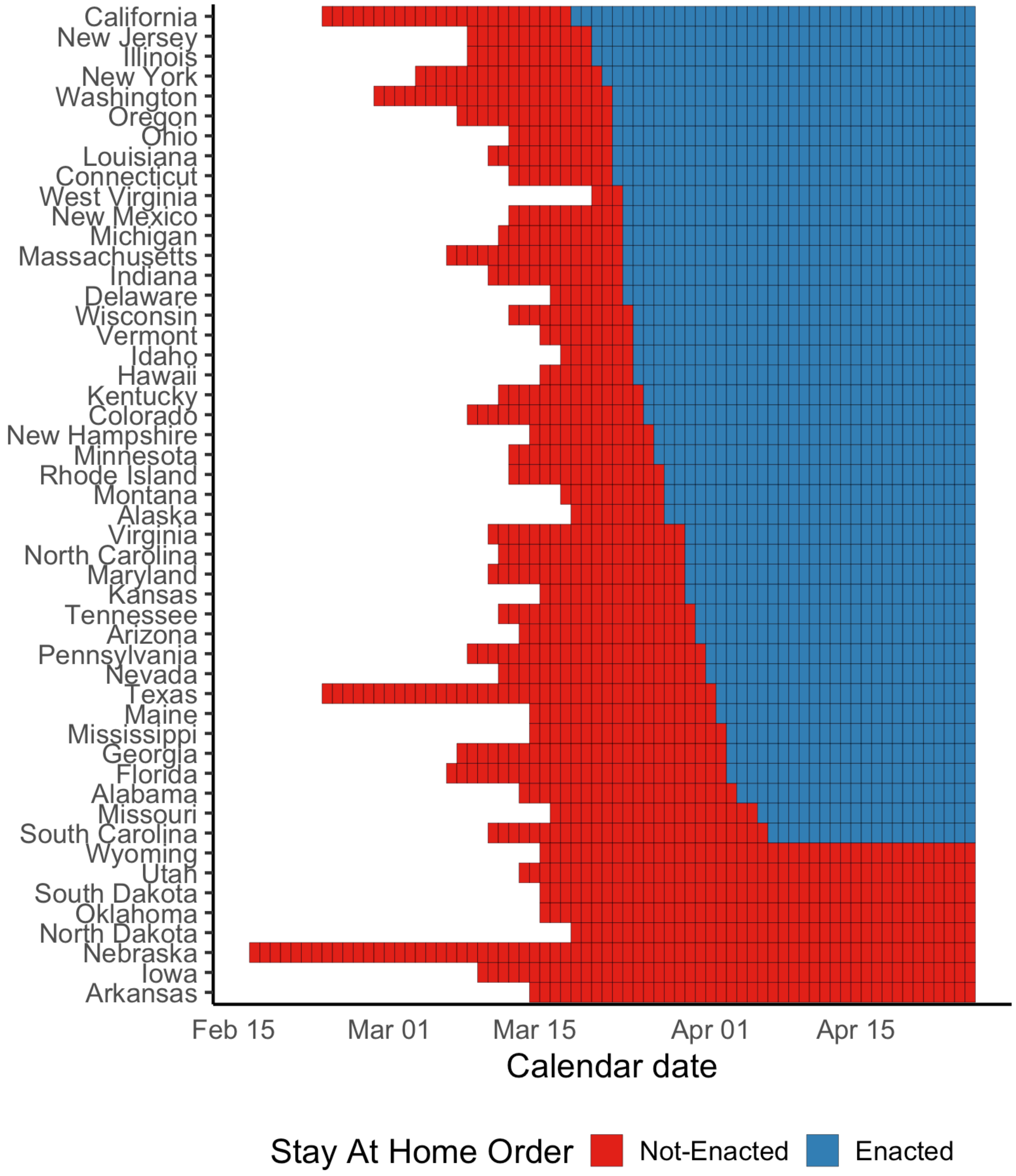
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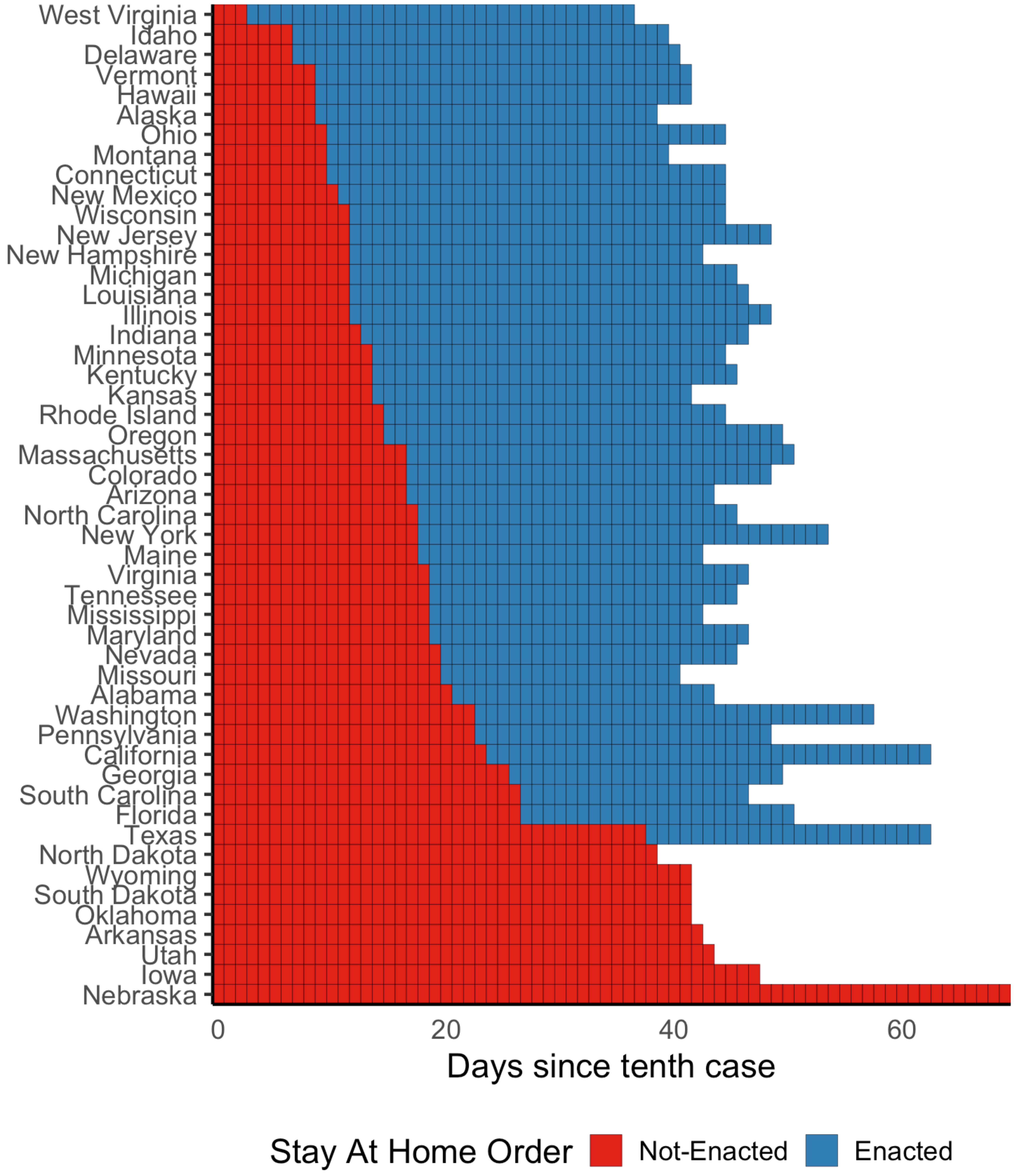
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Single and Nested Target Trials

Target trials

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- Staggered adoption of policies

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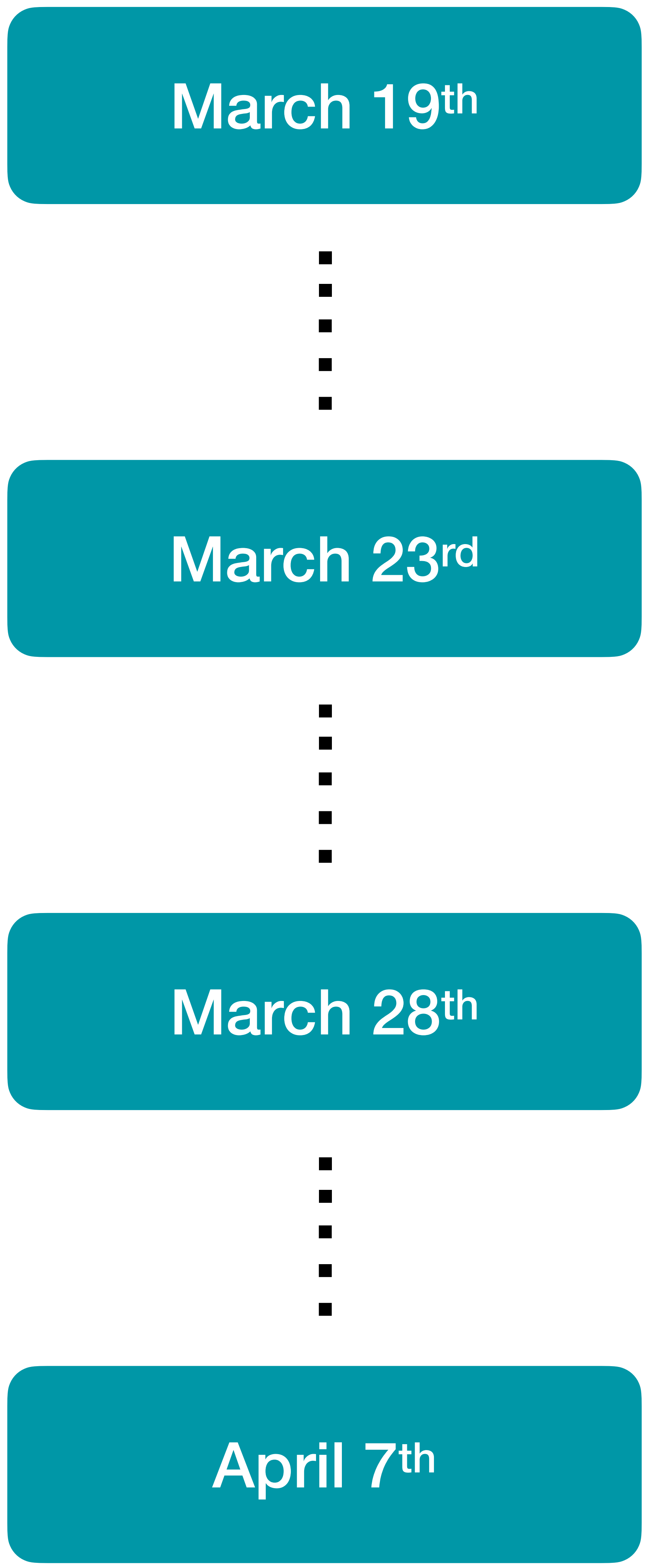
- Create cohorts by adoption date



Target trials

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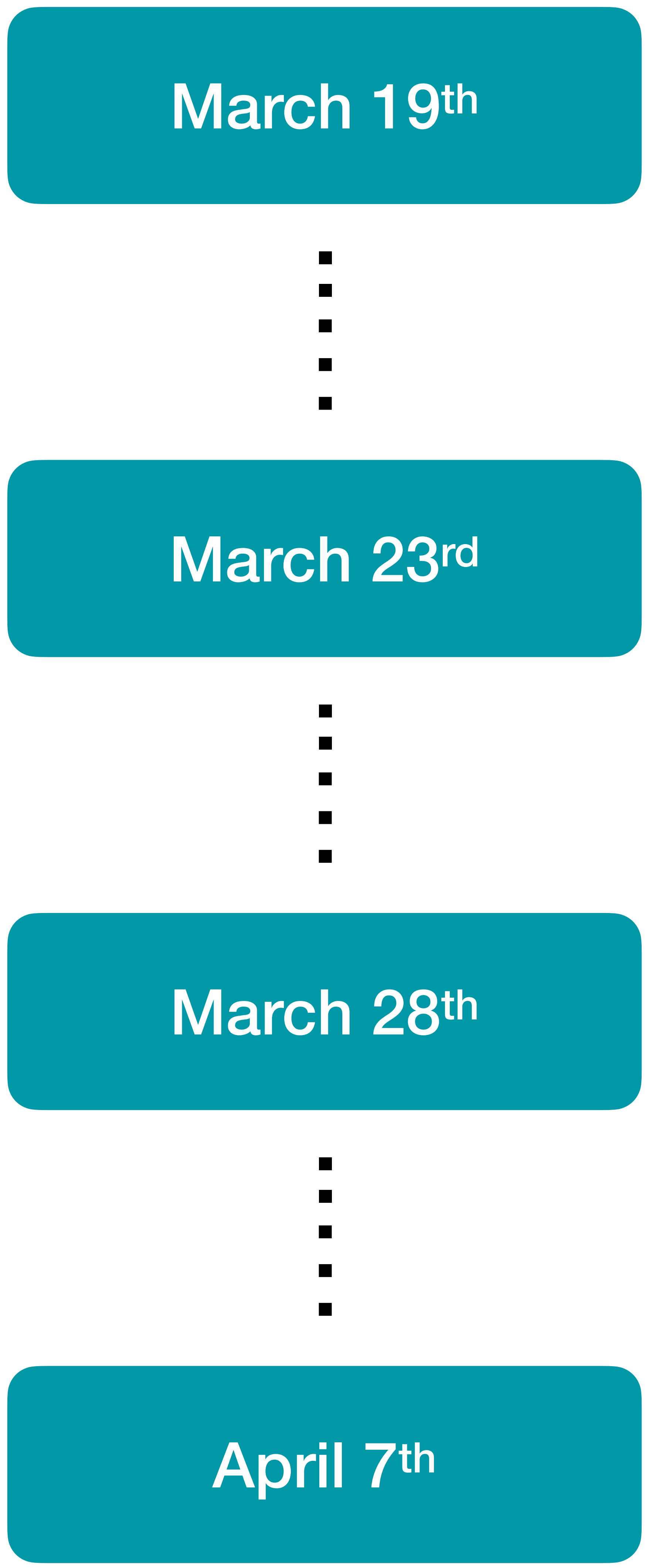
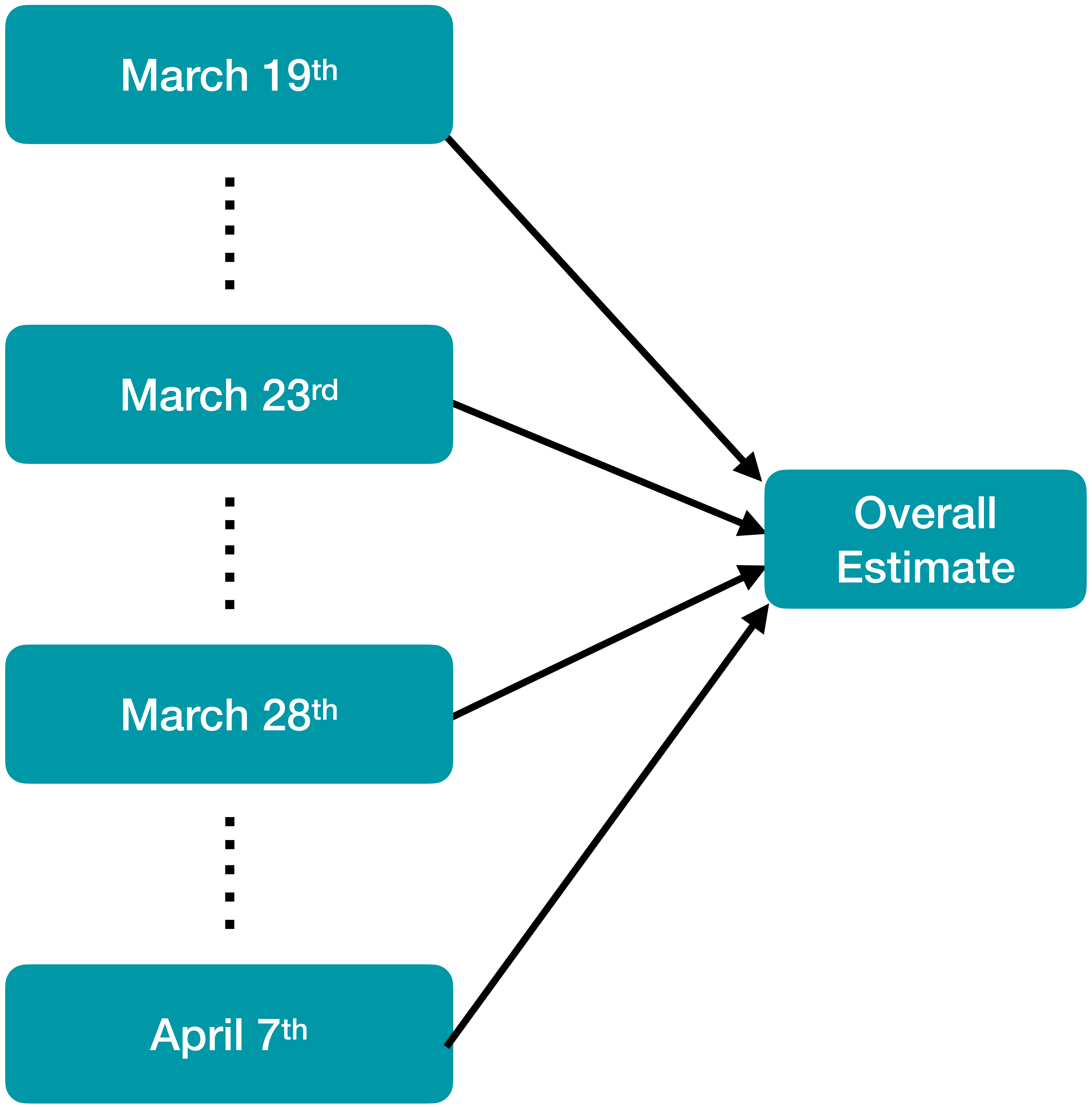


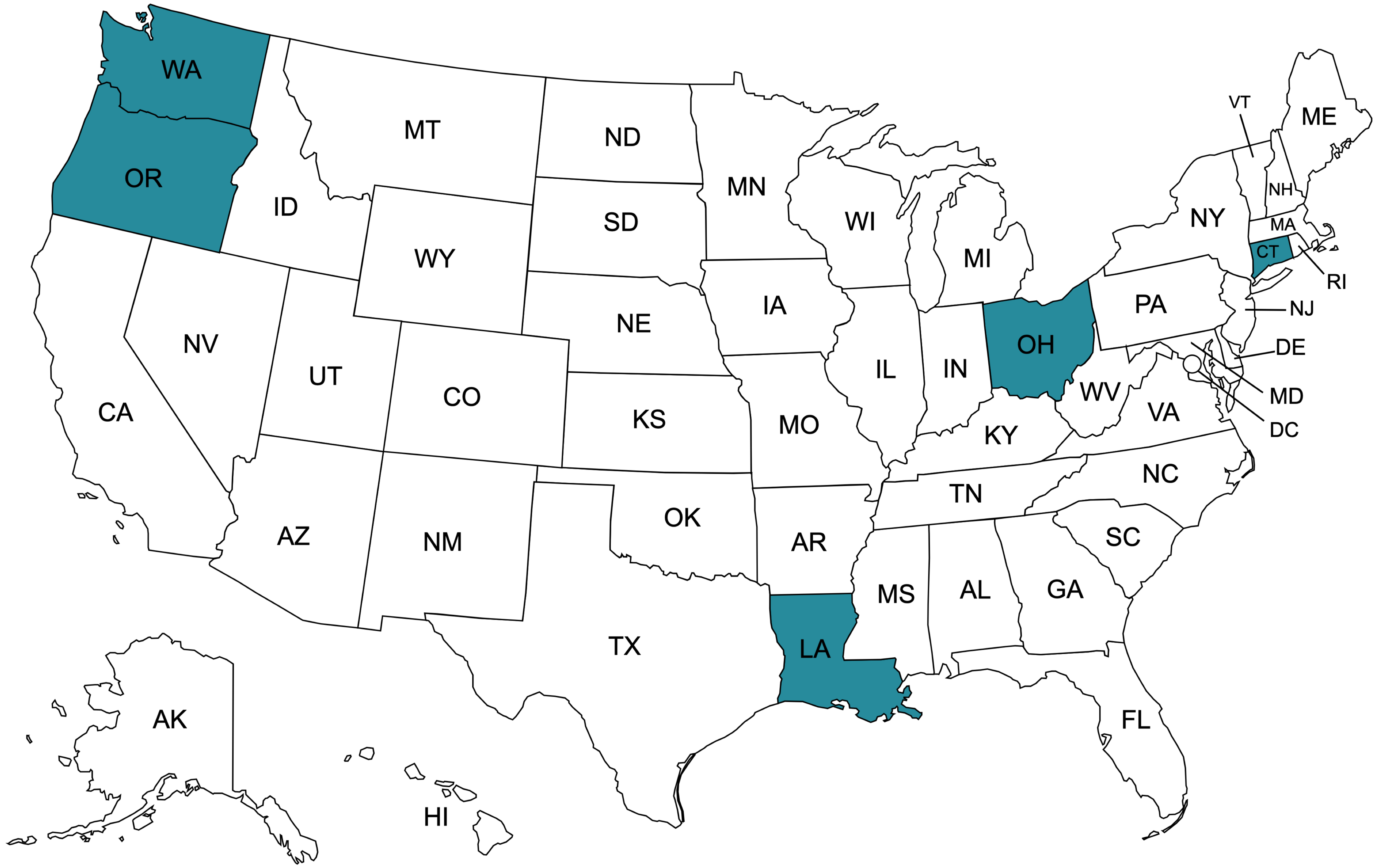
Target trials

- Staggered adoption of policies
- Create cohorts by adoption date
- Measure the effect for each cohort
- Aggregate across “single” target trials to a “nested” target trial



A single target trial

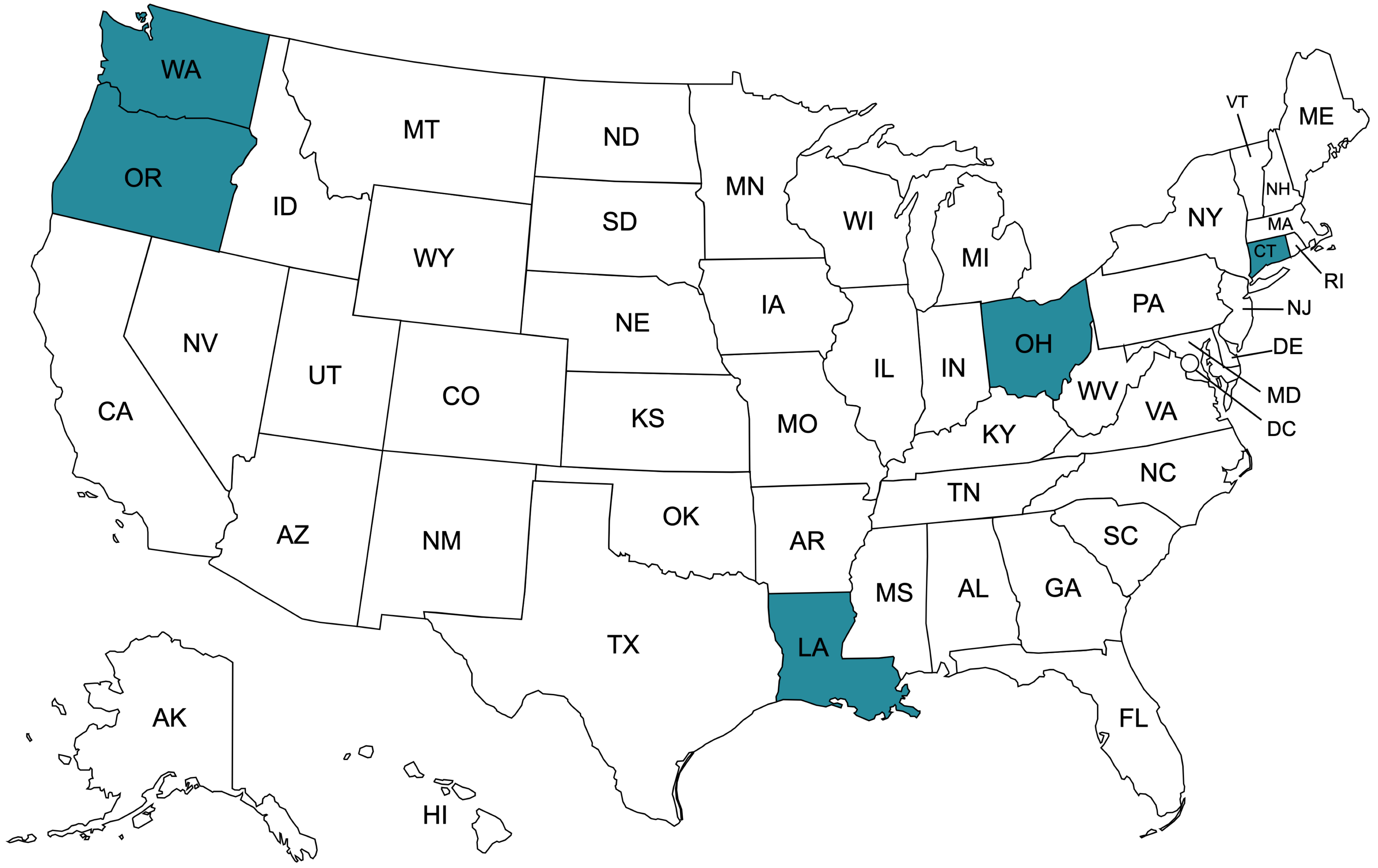
March 23rd Cohort



A single target trial

March 23rd Cohort

- What comparison states do we use?



A single target trial

March 23rd Cohort

- What comparison states do we use?
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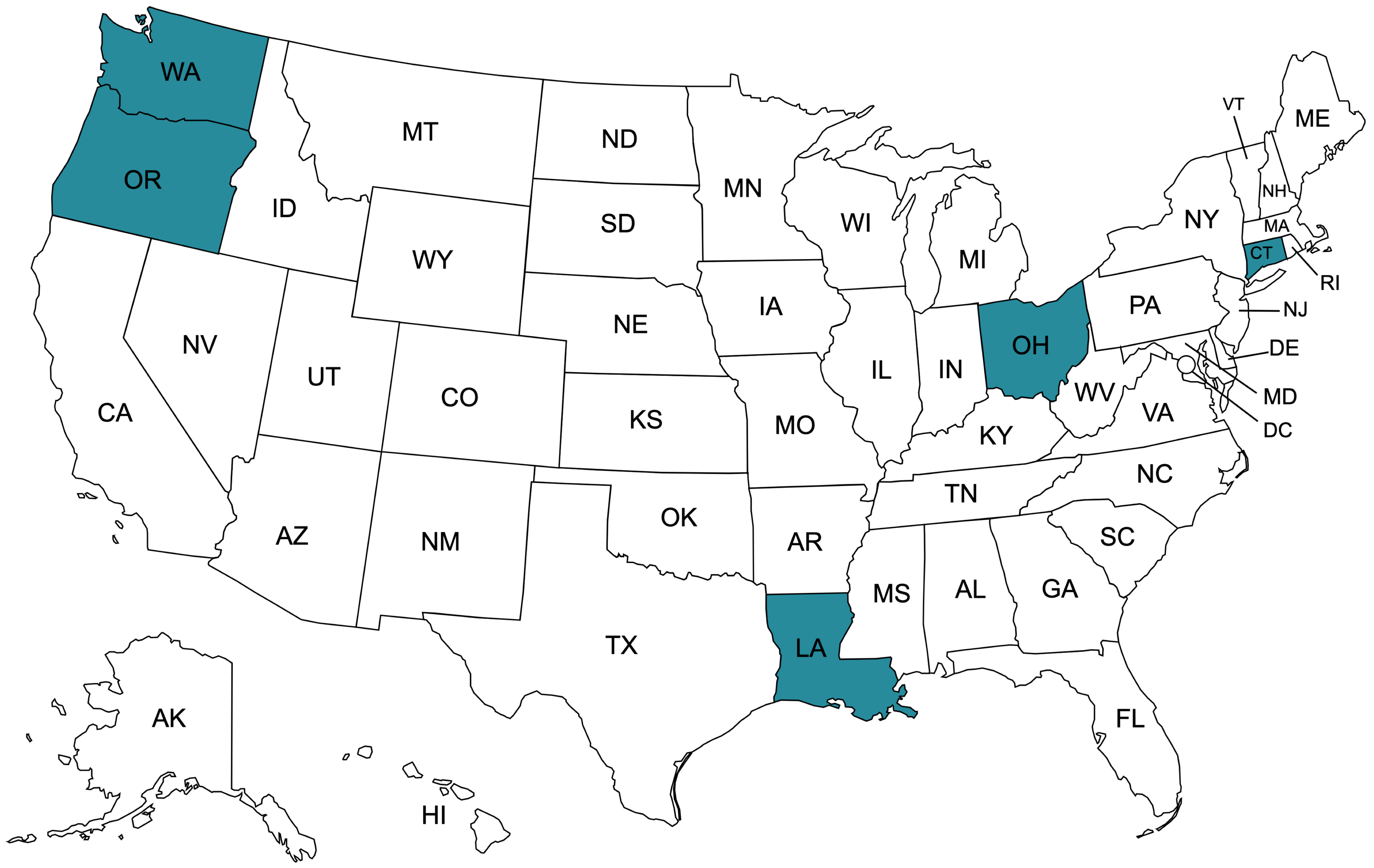
  - Only 19 days between first and last adopters
  - Expect effects to be delayed



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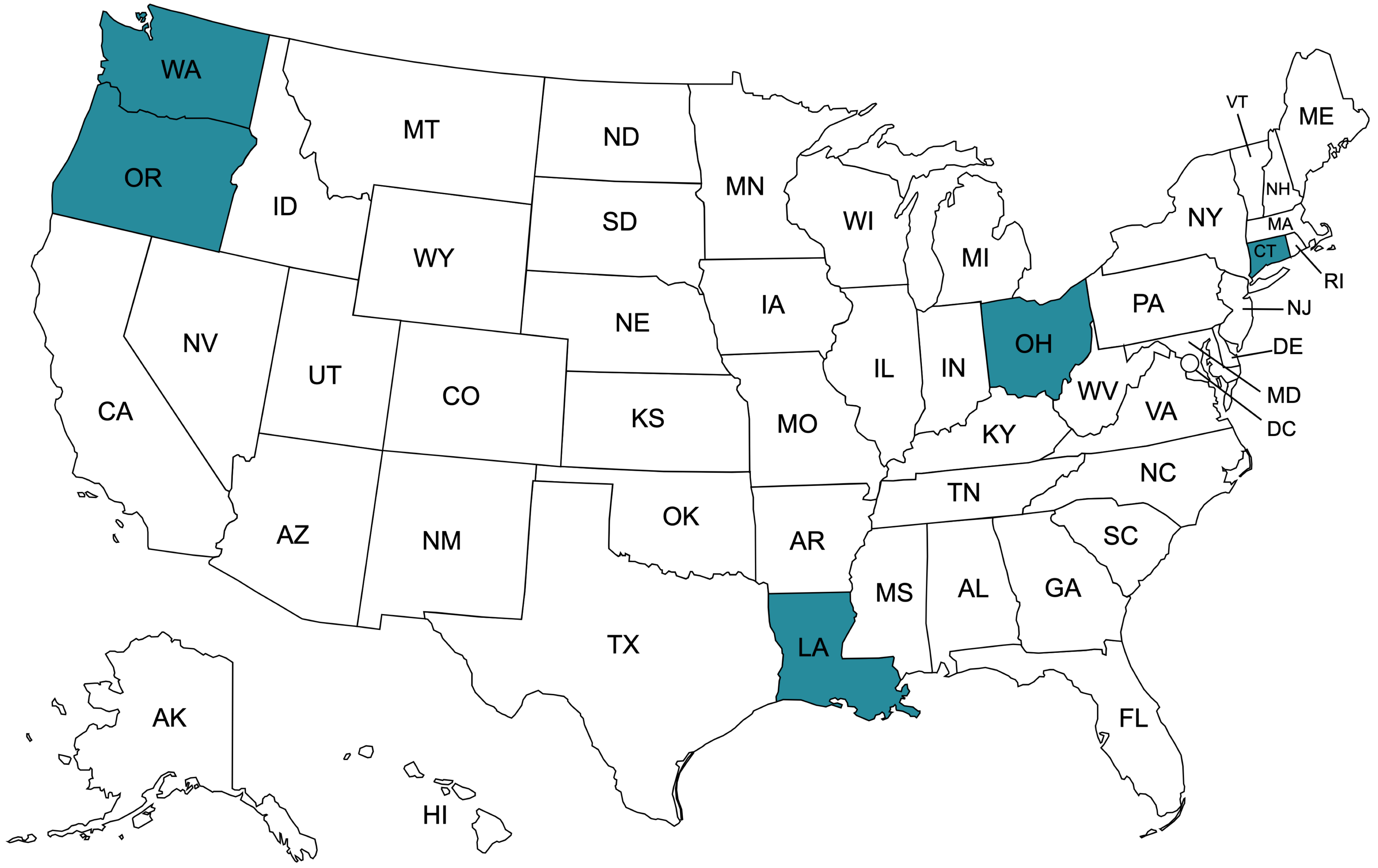

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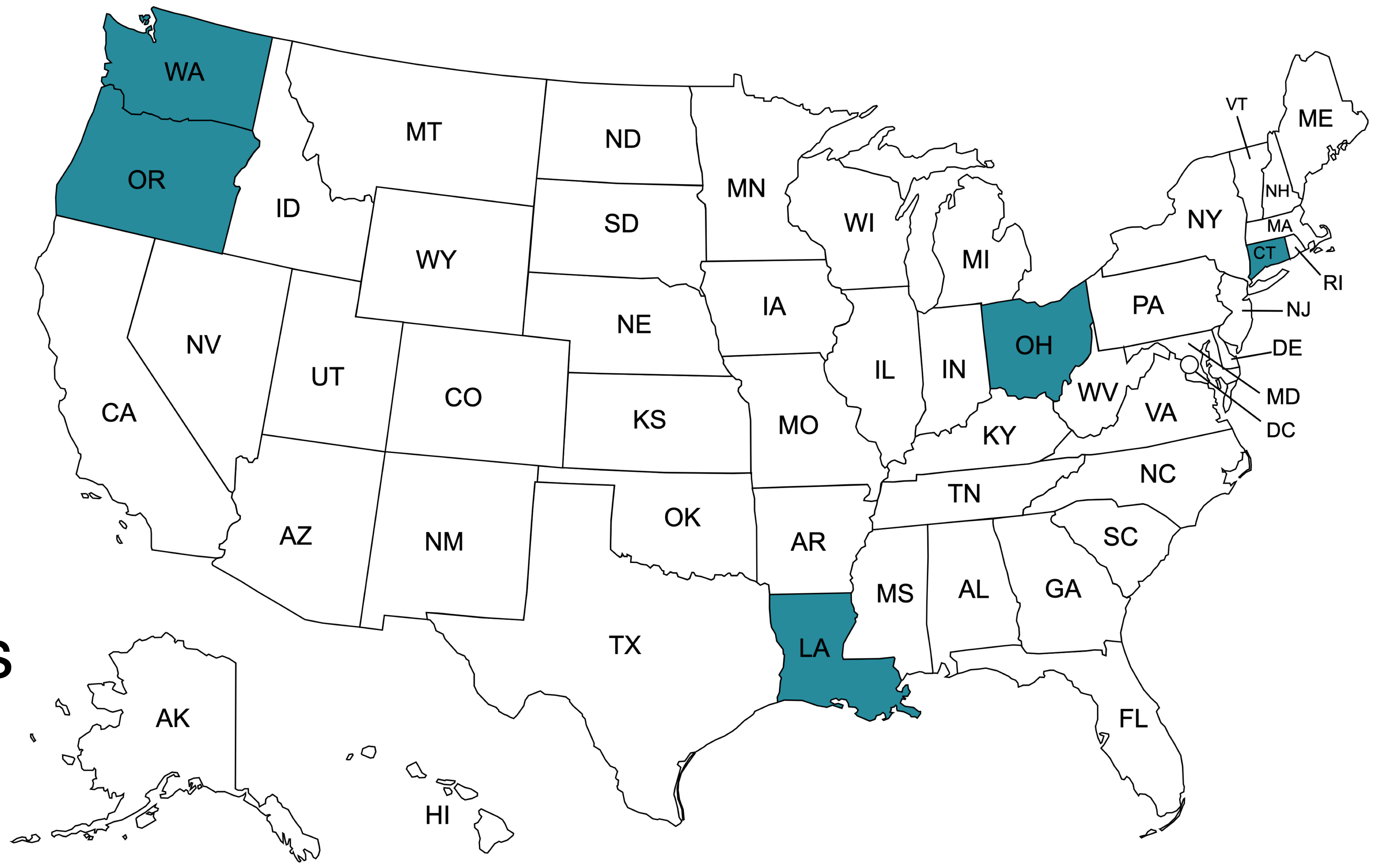
- Alternative: dynamic comparison groups
  - Need to assess assumptions for all groups
  - Are changes in effects just changes in comparison group?



Analysis: Differences in Differences

Key assumption: parallel trends

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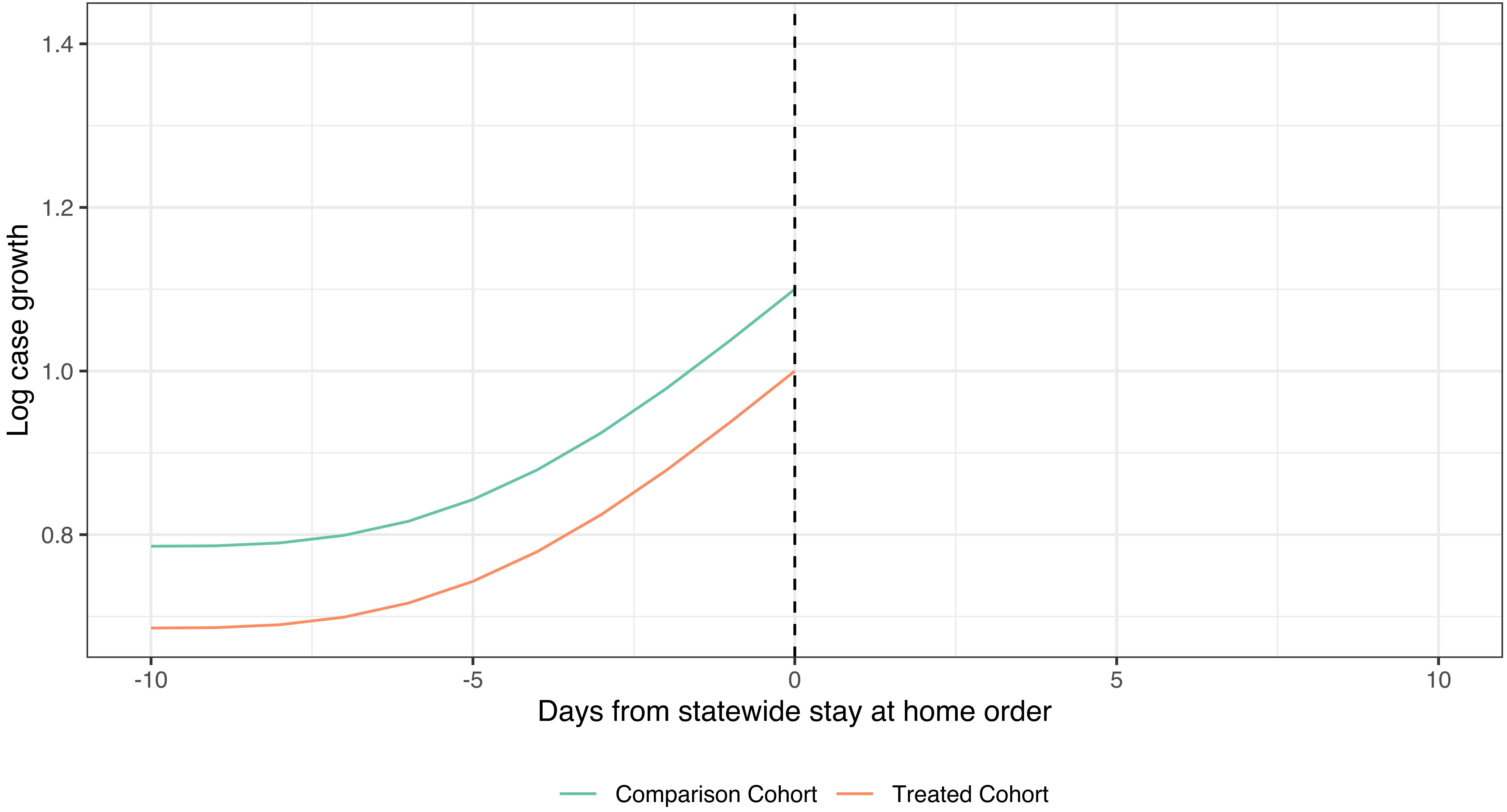

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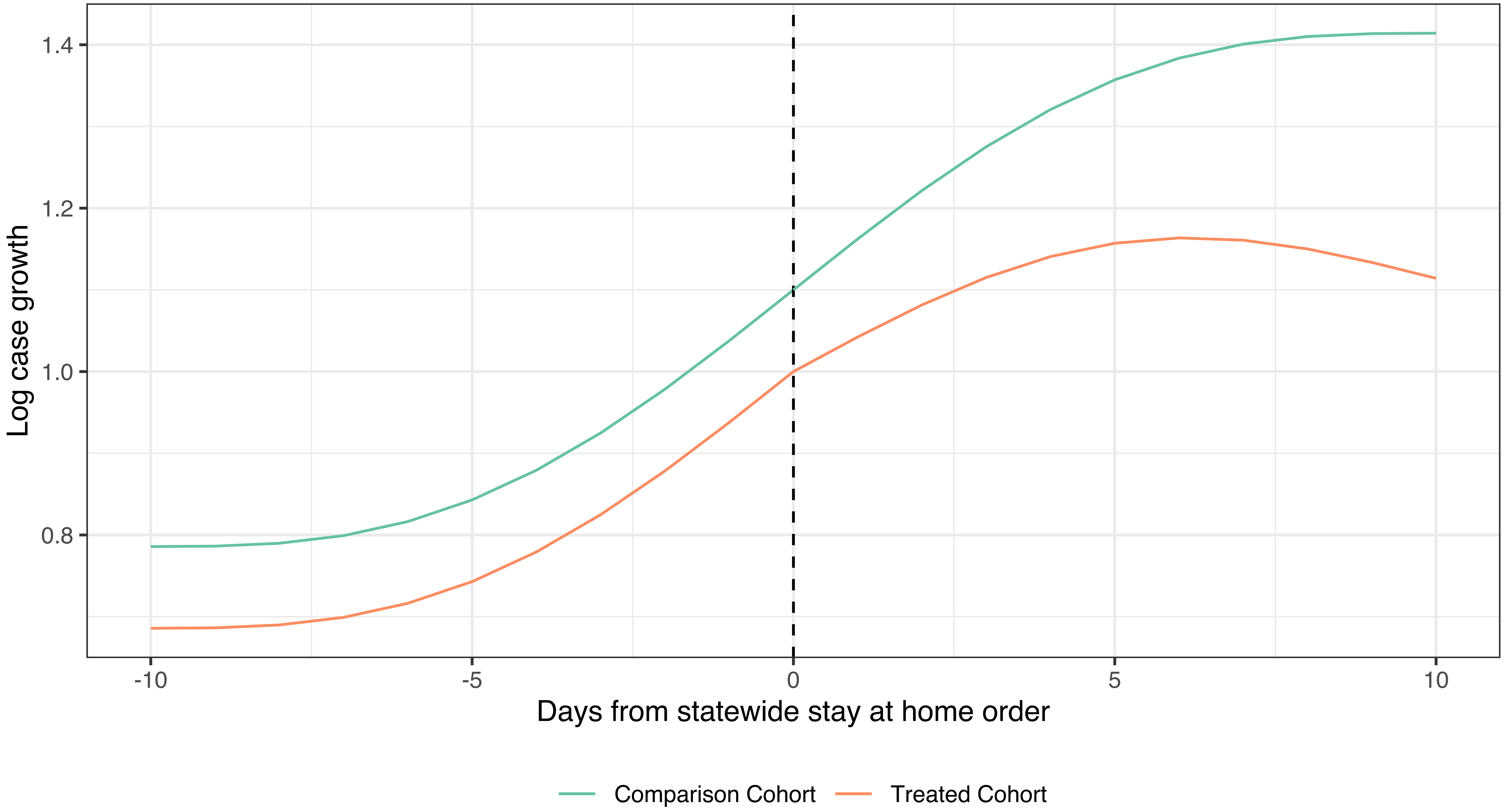

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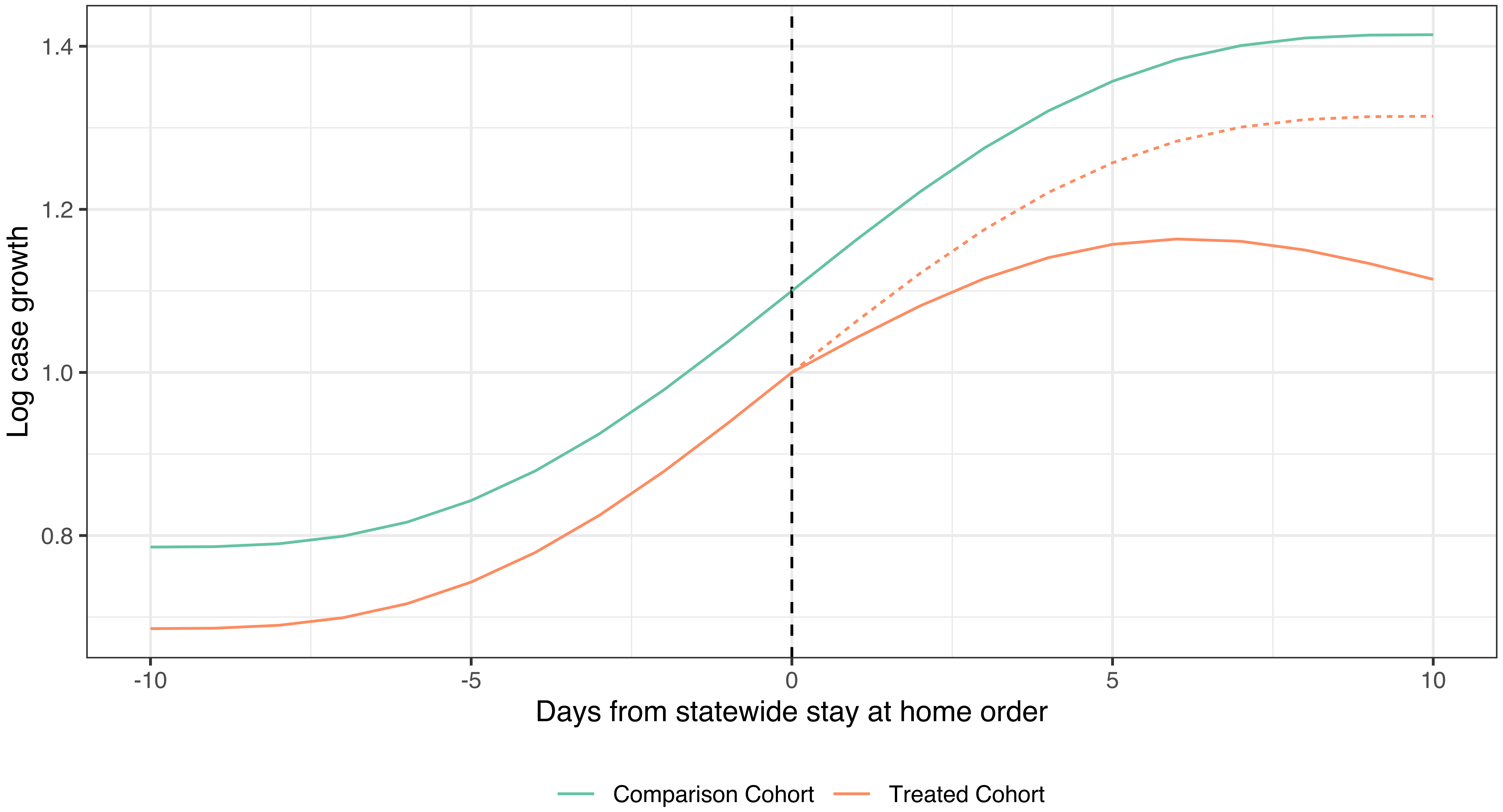

Estimating effects in a single target trial

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	Stay-at-Home Order		*Difference*
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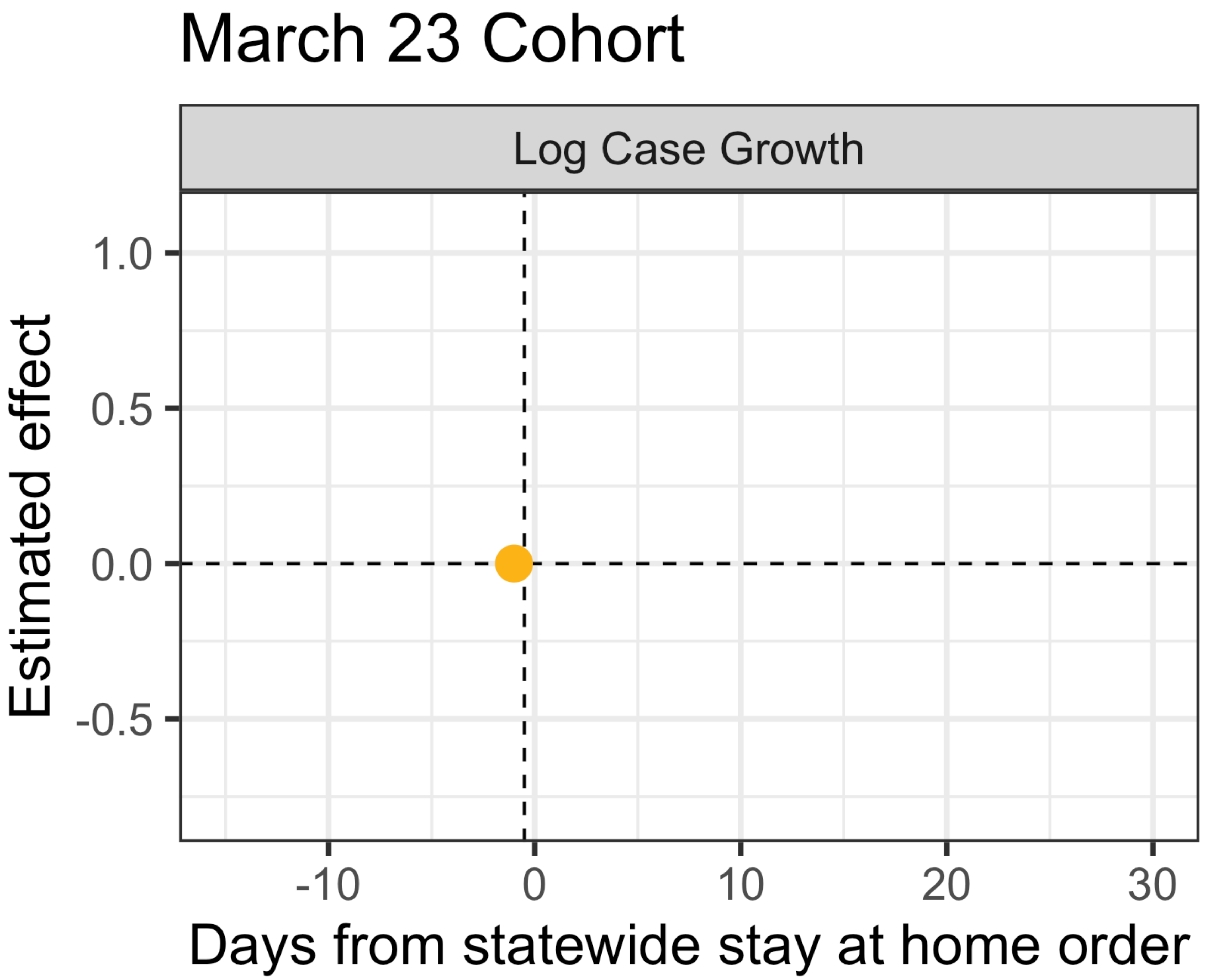

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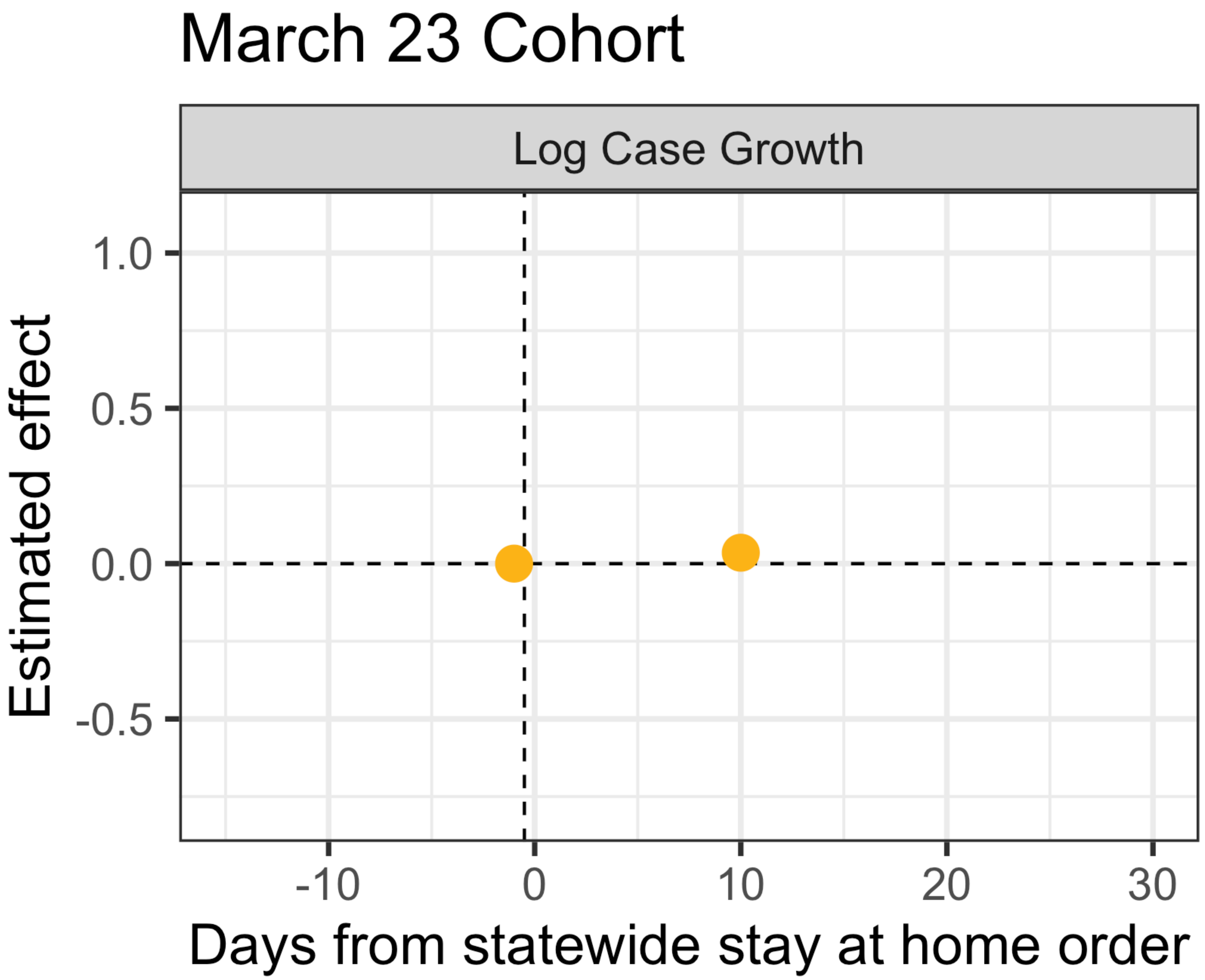

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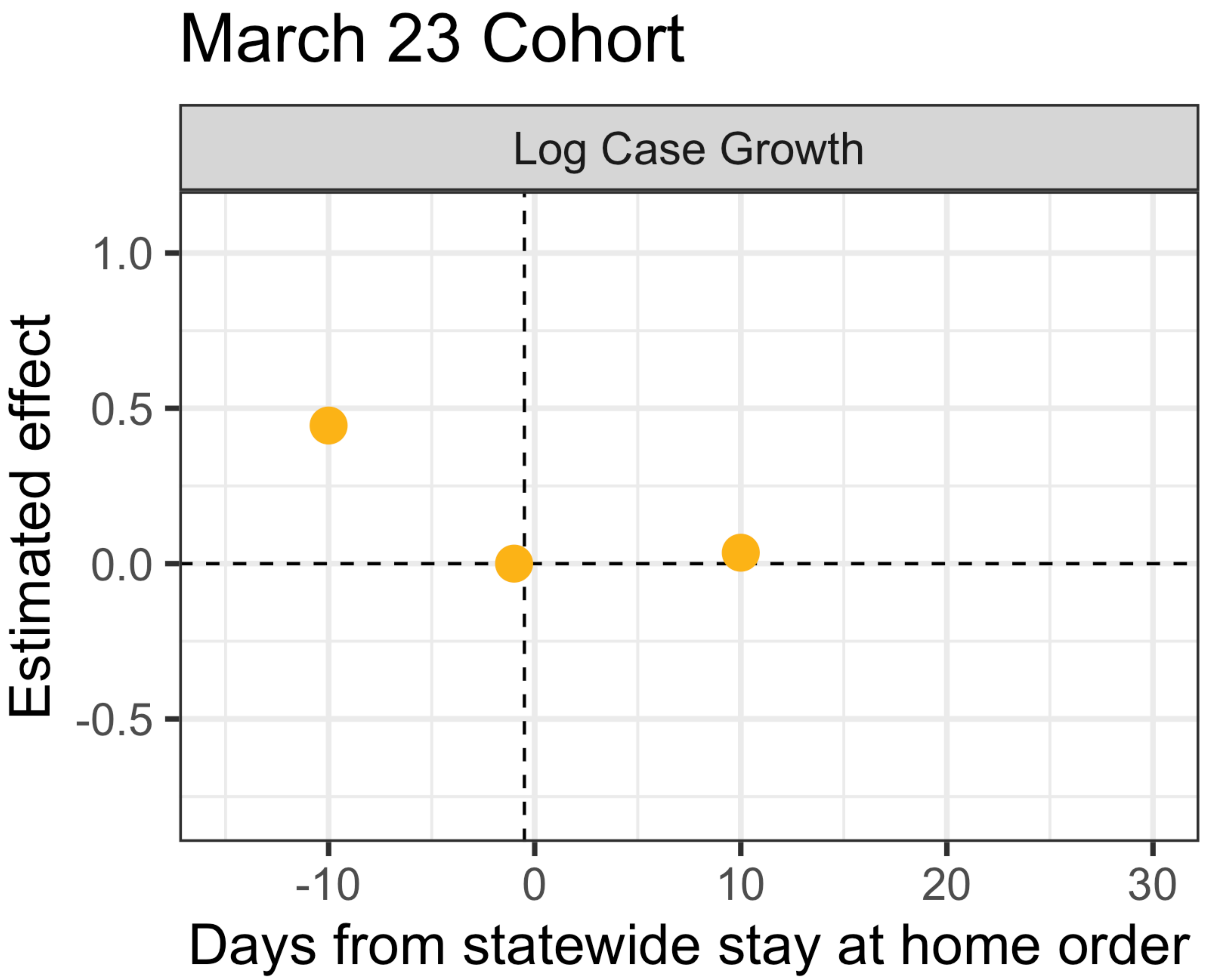

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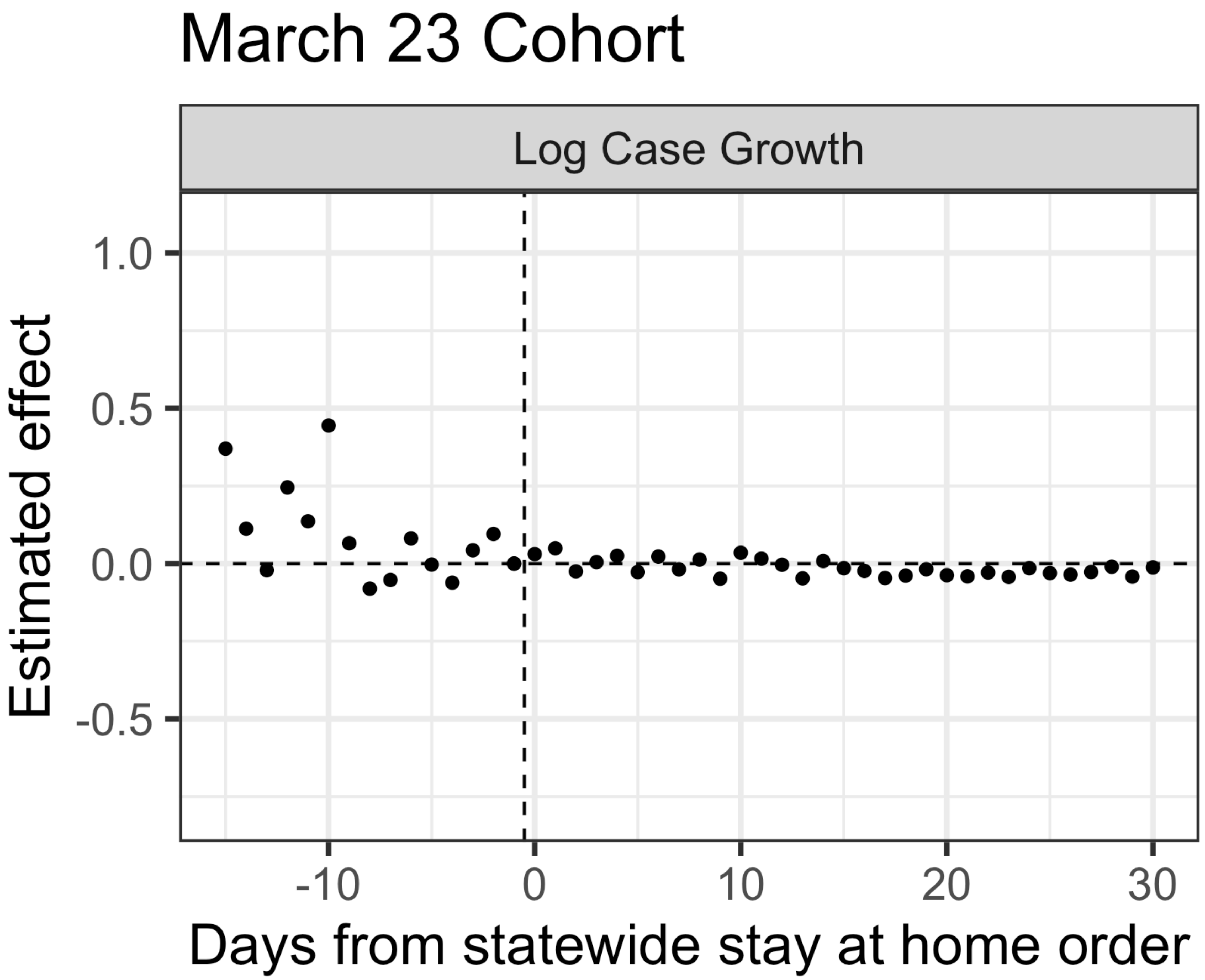

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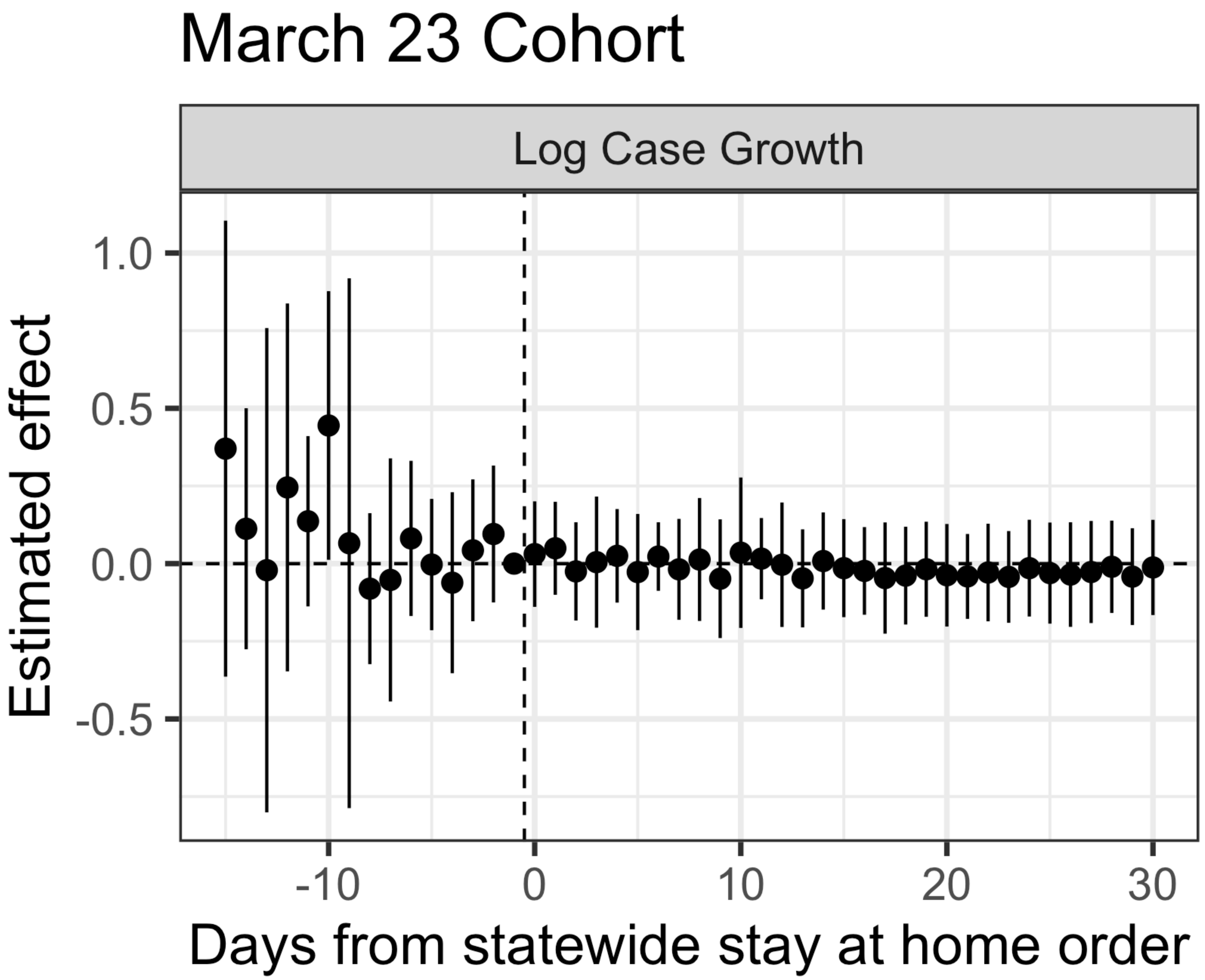

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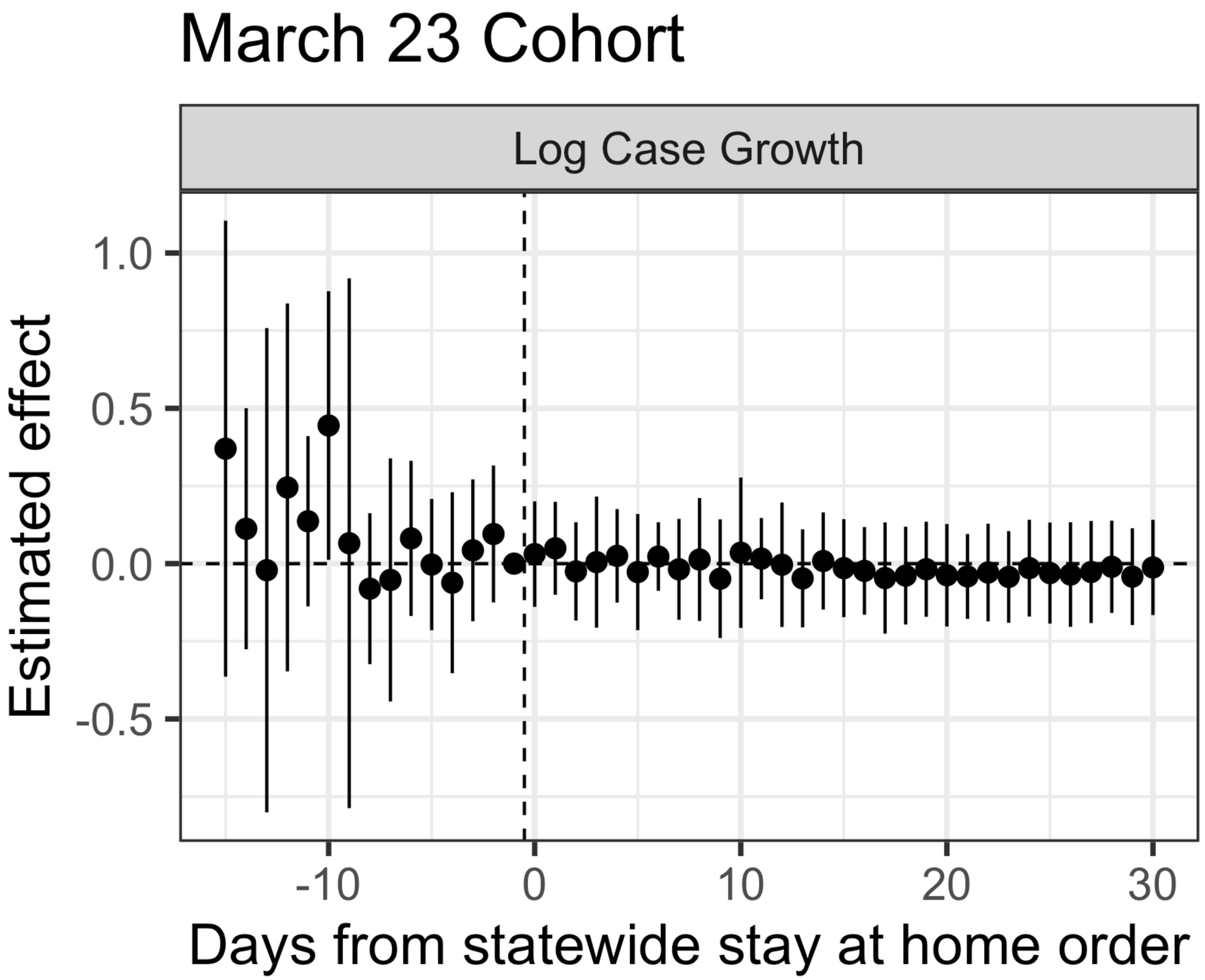

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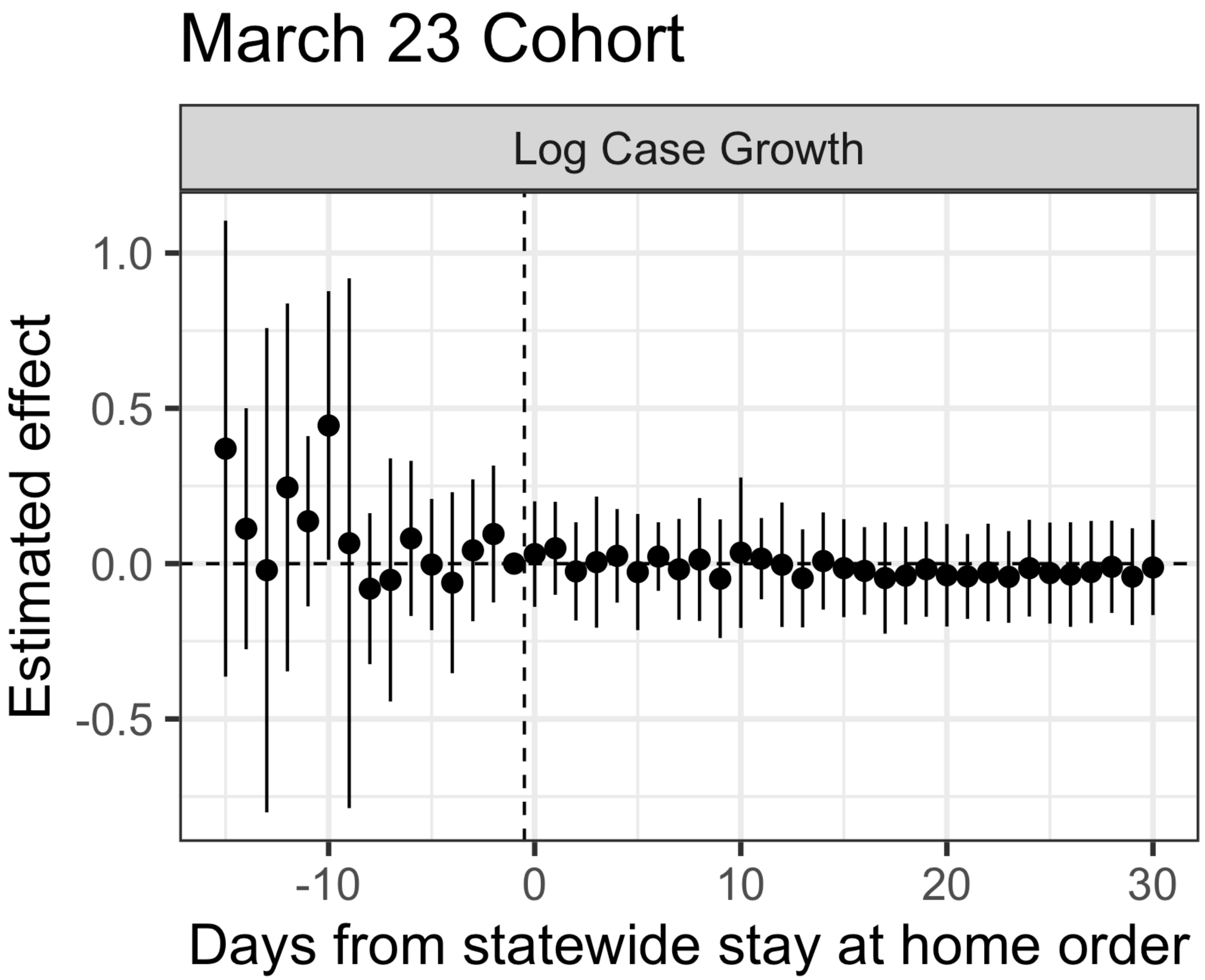
- Allows for a diagnostic check
  - Pre-period should have **zero** effect
- Possible violations of // trends
  - Anticipation, time-varying confounding



From single to nested target trials

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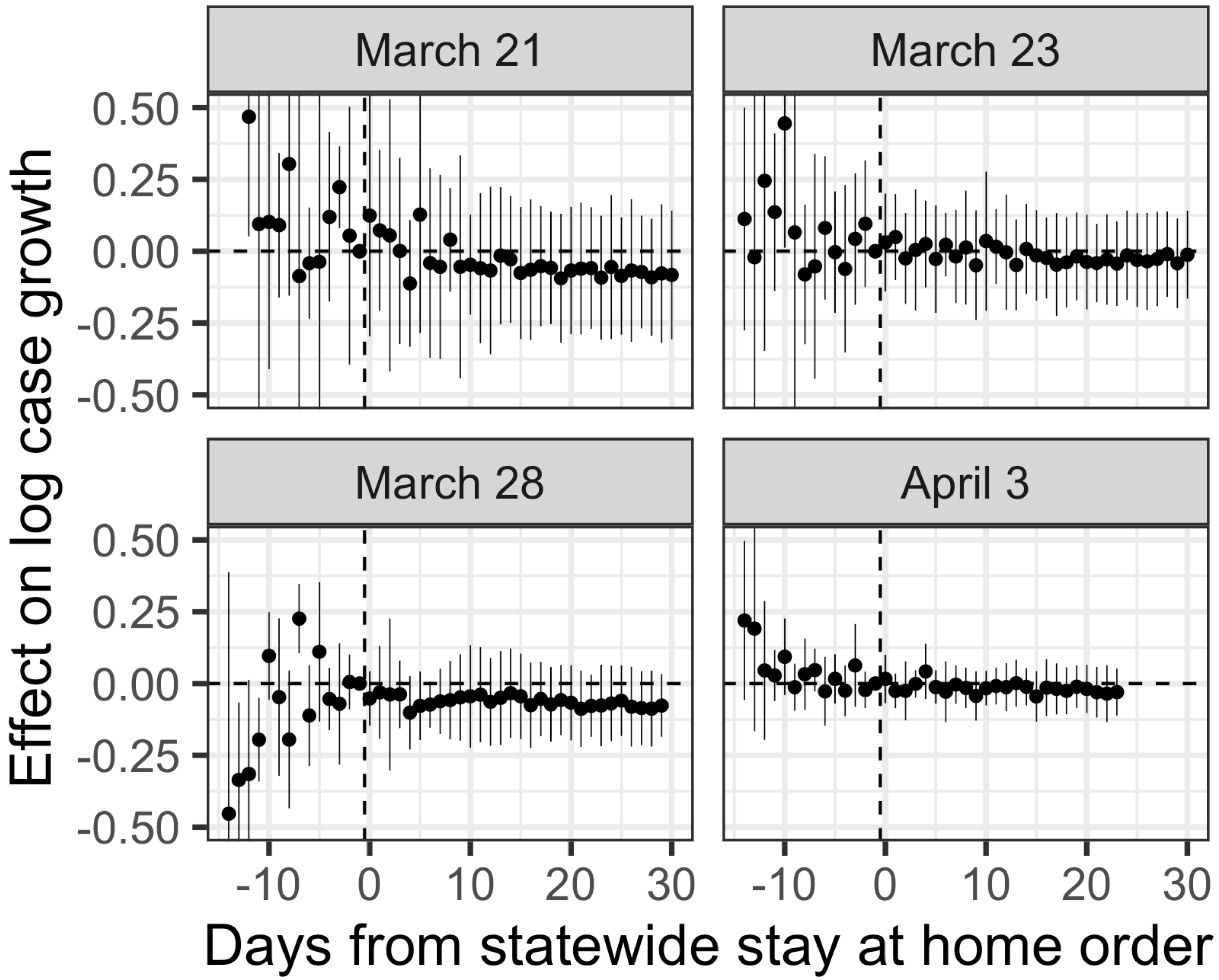
- Each single trial is different
  - Starting point, length of follow up, etc.

[Hernán et al 2016]



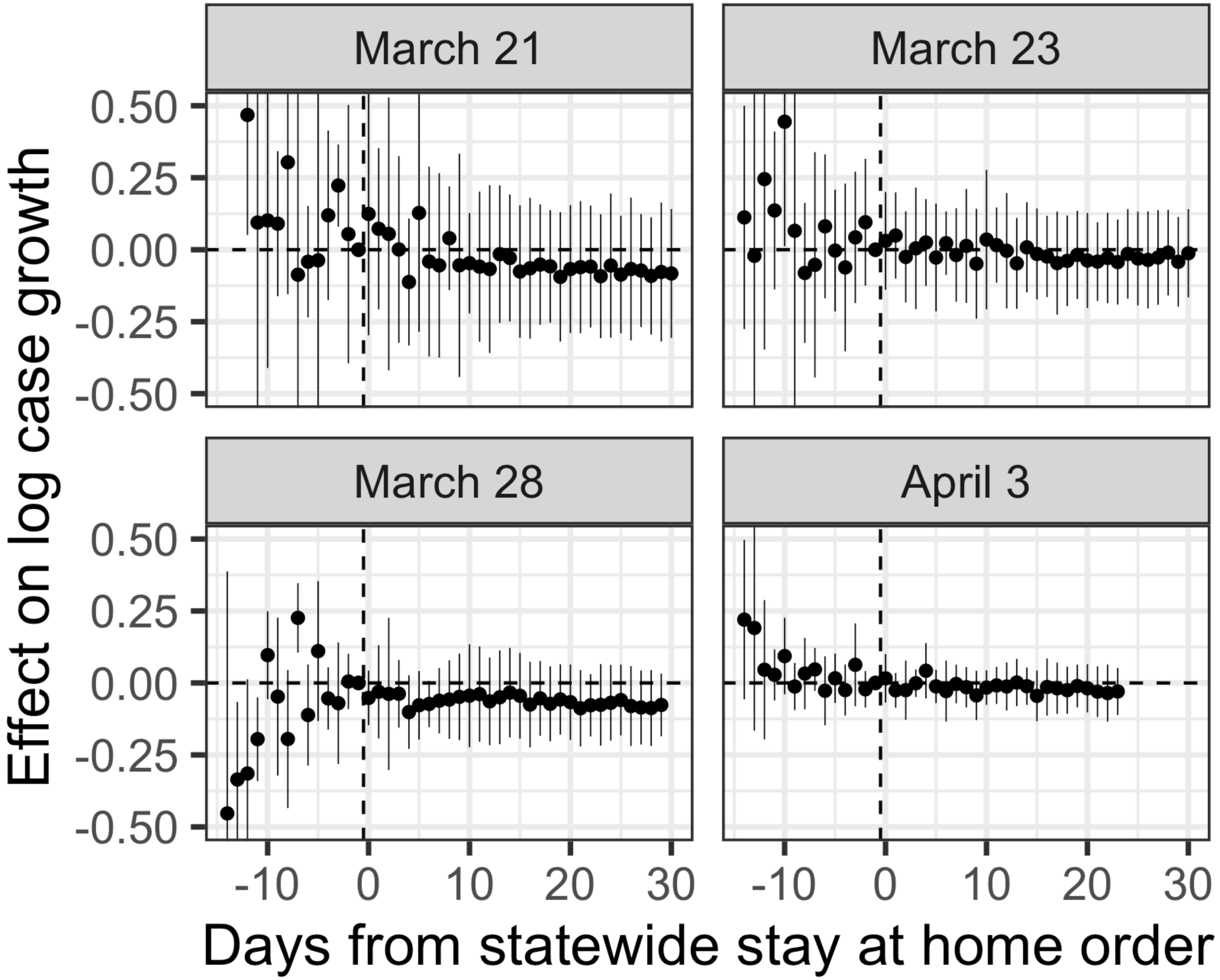
From single to nested target trials

- Each single trial is different
  - Starting point, length of follow up, etc.

[Hernán et al 2016]

- Take a size-weighted average

$$\widehat{DID}_k = \frac{1}{n_1}\sum_{g=1}^{G} n_{1g}\widehat{DID}_{kg}$$



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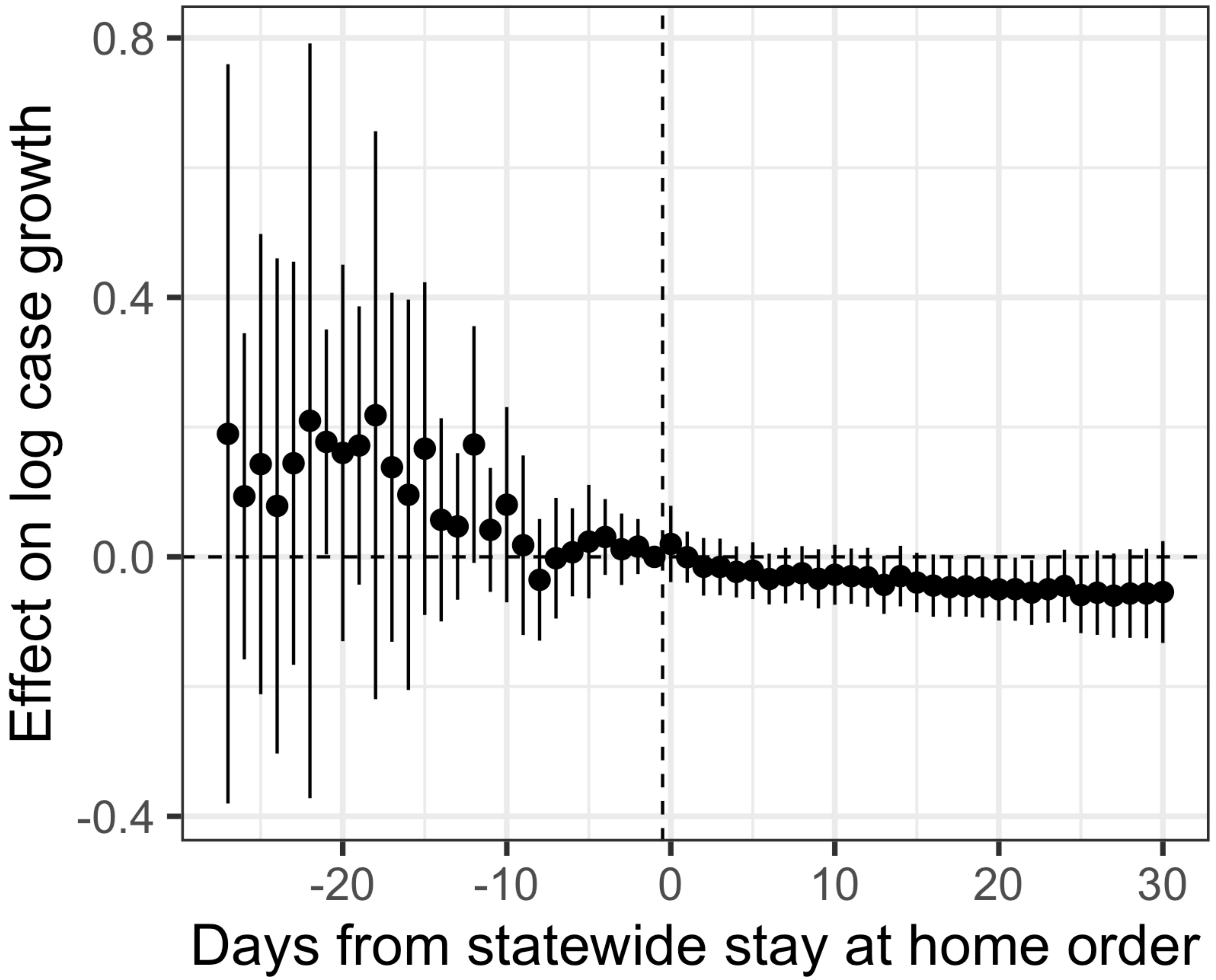

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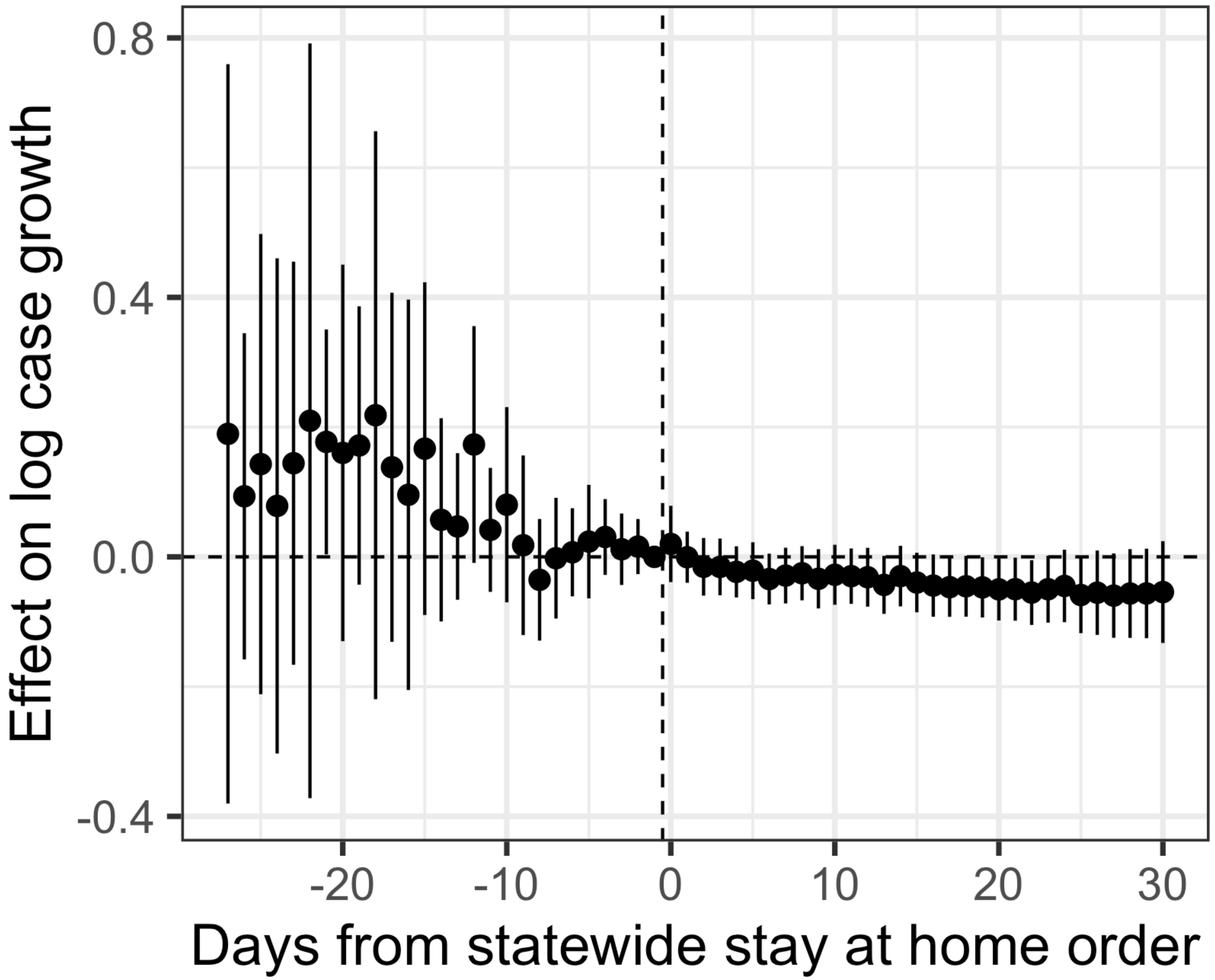
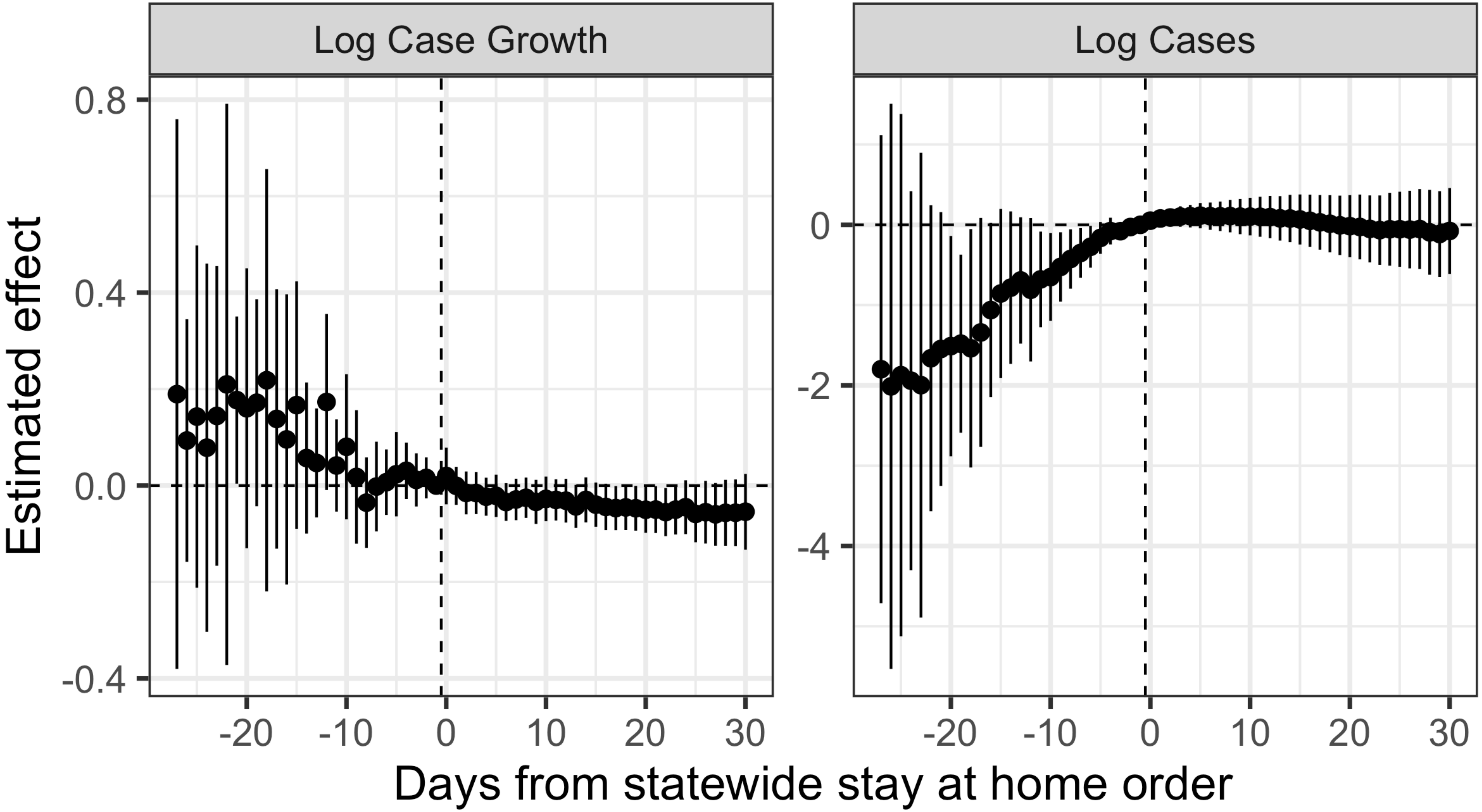
- Recovers “stacked” DiD

- Uncertainty quantification is tricky
  - Various forms of resampling methods

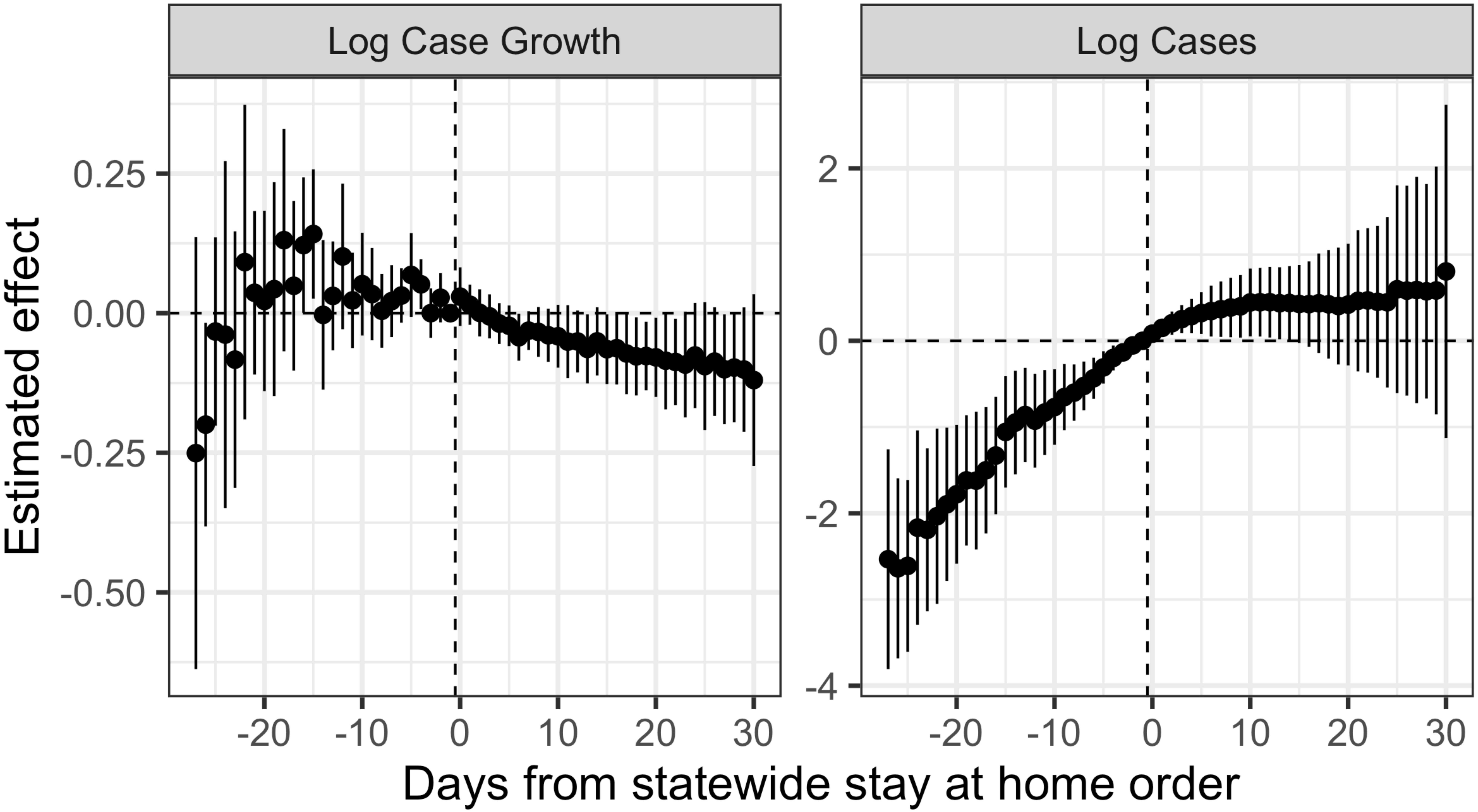
[Abraham & Sun 2021; Callaway & Sant’Anna 2021]



Plausibility of // trends depends on outcome



Slight differences when using case time



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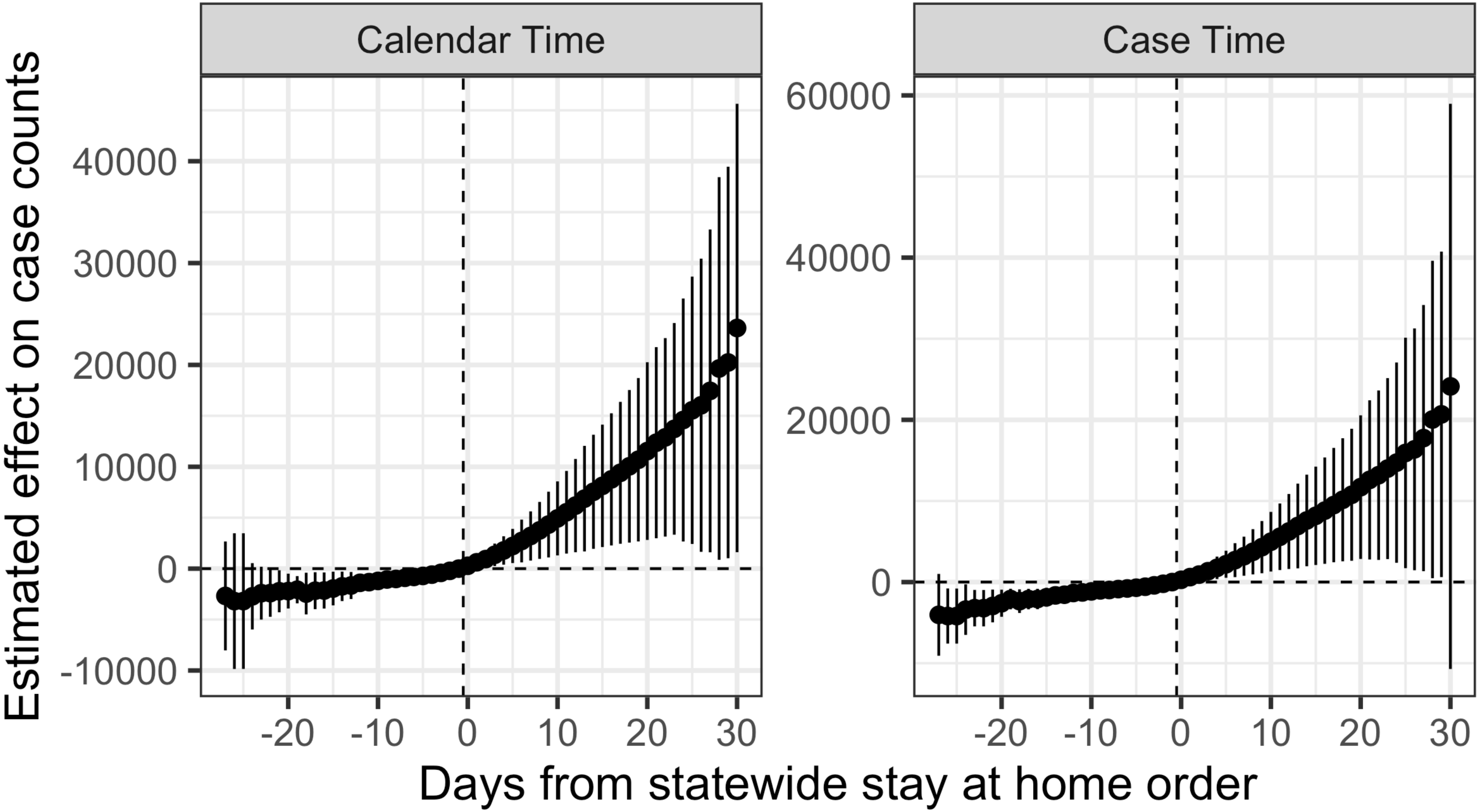
Thank you!

ebenmichael.github.io

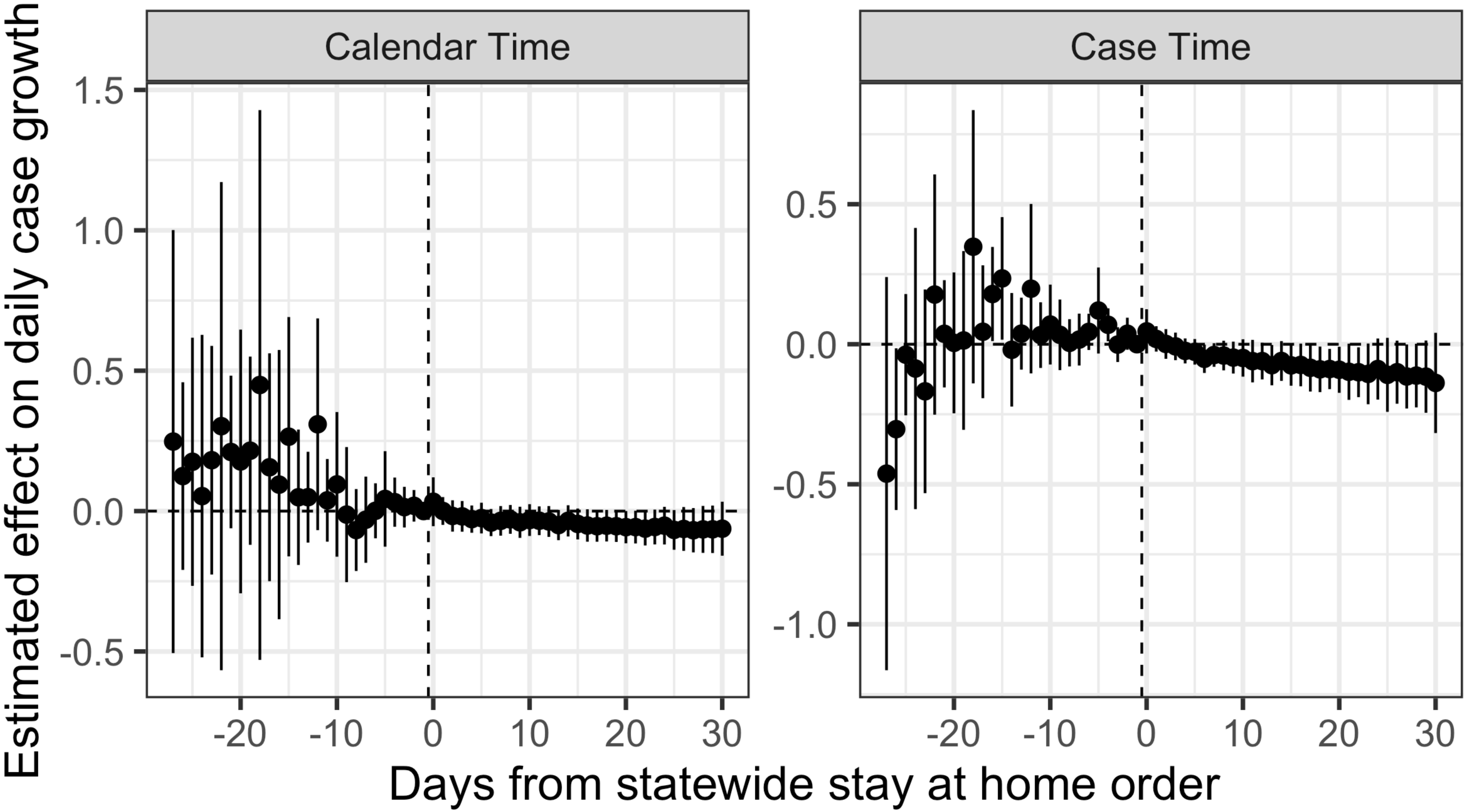
Ben-Michael, E., Feller, A., & Stuart, E. A. (2021). A Trial Emulation Approach for Policy Evaluations with Group-level Longitudinal Data. Epidemiology, 32(4), 533–540.

Appendix

Raw case count estimates



Case ratio estimates



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