Rescuing impact measurements

Differential treatment timing and duration in d-i-d estimation

2024-09-18

Outline of presentation

- Background
- Problem
- Solutions
- Case study - MISTI
- Final thoughts

Bottom line up front

- The difference-in-differences estimator can generalize to multiple treatment groups and multiple time periods
- However, under certain conditions that we only realized recently, this can introduce bias
- Examine the different groups created by differential timing
- Use event study designs and other newer estimators that account for this bias

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What is the canonical d-i-d setup?

$$y_{it} = \beta_0 + \delta_{0,t} Post_t + \beta_{1,i} Treat_i + \delta_{1,it} Post_t * Treat_i + \epsilon_{it}$$

where..

β_0 is the comparison group at baseline

δ_0 is the secular change from baseline to endline, unrelated to treatment

β_1 is the difference between the treatment and comparison groups at baseline, and

δ_1 is the treatment effect, the interaction of treatment and time

Algebraically, δ_0 can be expressed as the difference between the pre/post difference in each of the treatment and comparison groups

$$\delta_1 = (\bar{y}_{POST,TREAT} - \bar{y}_{PRE,TREAT}) - (\bar{y}_{POST,COMPARISON} - \bar{y}_{PRE,COMPARISON})$$

hence, difference-in-differences (d-i-d or DiD or DD)

Canonical d-i-d, 2x2

$$y_{it} = \beta_0 + \delta_{0,t} Post_t + \beta_{1,i} Treat_i + \delta_{1,it} Post_t * Treat_i + \epsilon_{it}$$

	Pre	**Post**	**Post - Pre**
Comparison	β_0	$\beta_0 + \delta_0$	δ_0
Treatment	$\beta_0 + \beta_1$	$\beta_0 + \delta_0 + \beta_1 + \delta_1$	$\delta_0 + \delta_1$
Treatment - Comparison	β_1	$\beta_1 + \delta_1$	δ_1

Generalizing d-i-d to many periods/groups

When we generalize to multiple time periods and/or groups, we have the two-way fixed effect (TWFE) estimator

$$y_{it} = \alpha_i + \alpha_t + \beta_{it}^{DD} + \epsilon_{it}$$

where..

α_i are group fixed effects

α_t are time fixed effects

B_{it}^{DD} indicates whether group *i* in period *t* is treated

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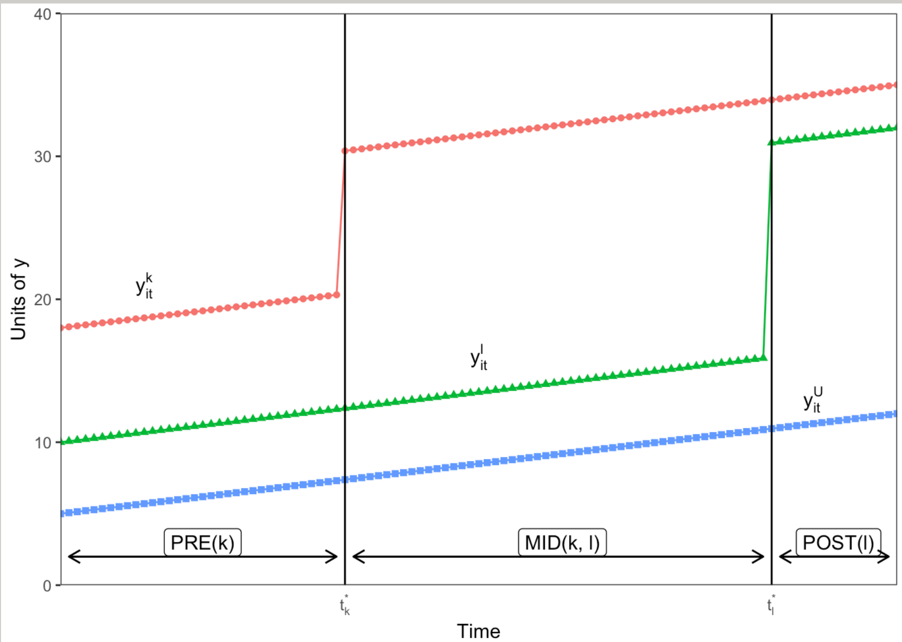
But what is β_{it}^{DD} actually telling us?

- For the canonical 2x2, we know exactly what we are estimating
- For *i* groups and *t* time periods, we are getting some average of multiple 2x2s
- But how does this work, exactly?

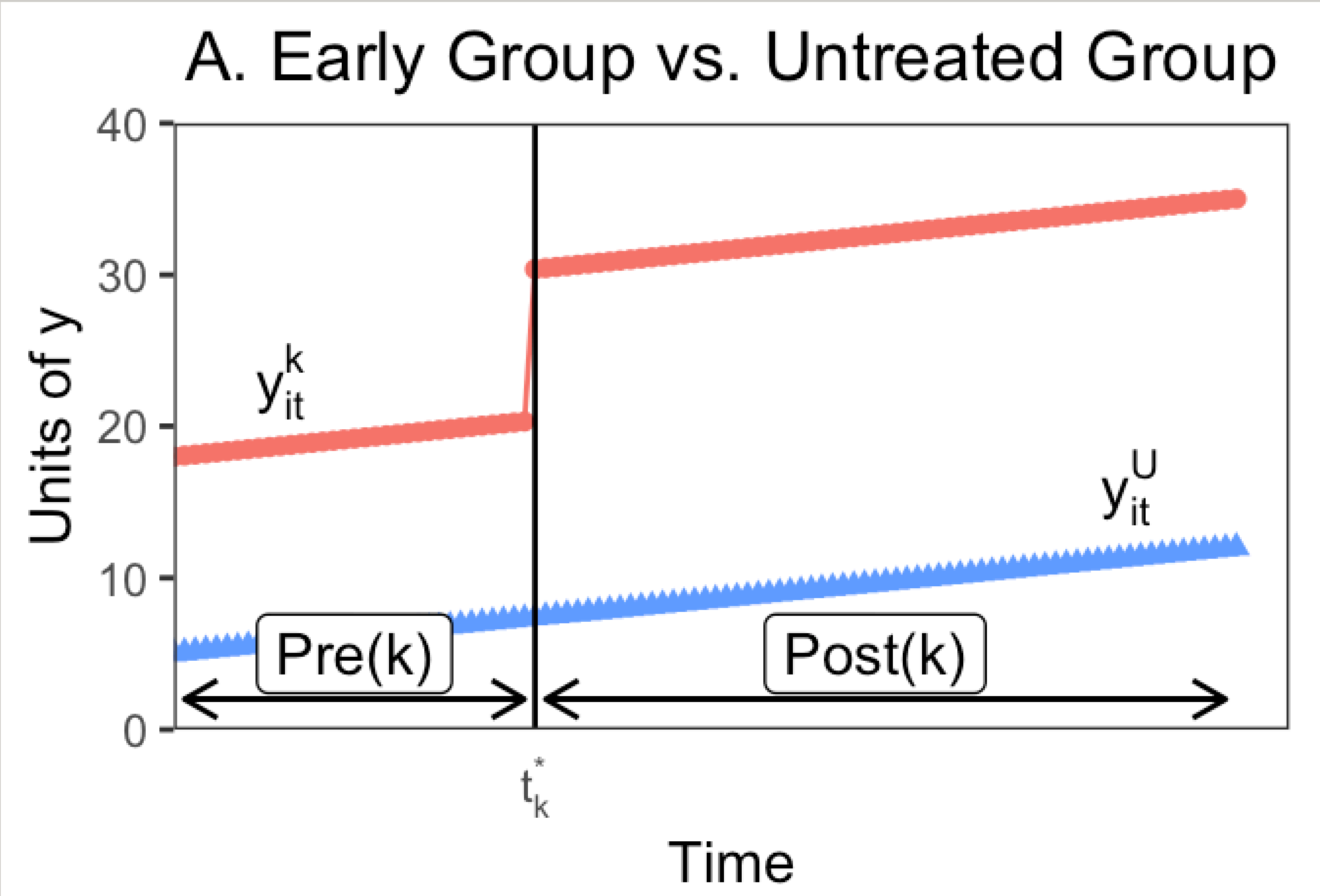
Two treatment groups, early and late

Let's take a single step from two time periods to three, where treatment can be adopted at either t = 2 or t = 3

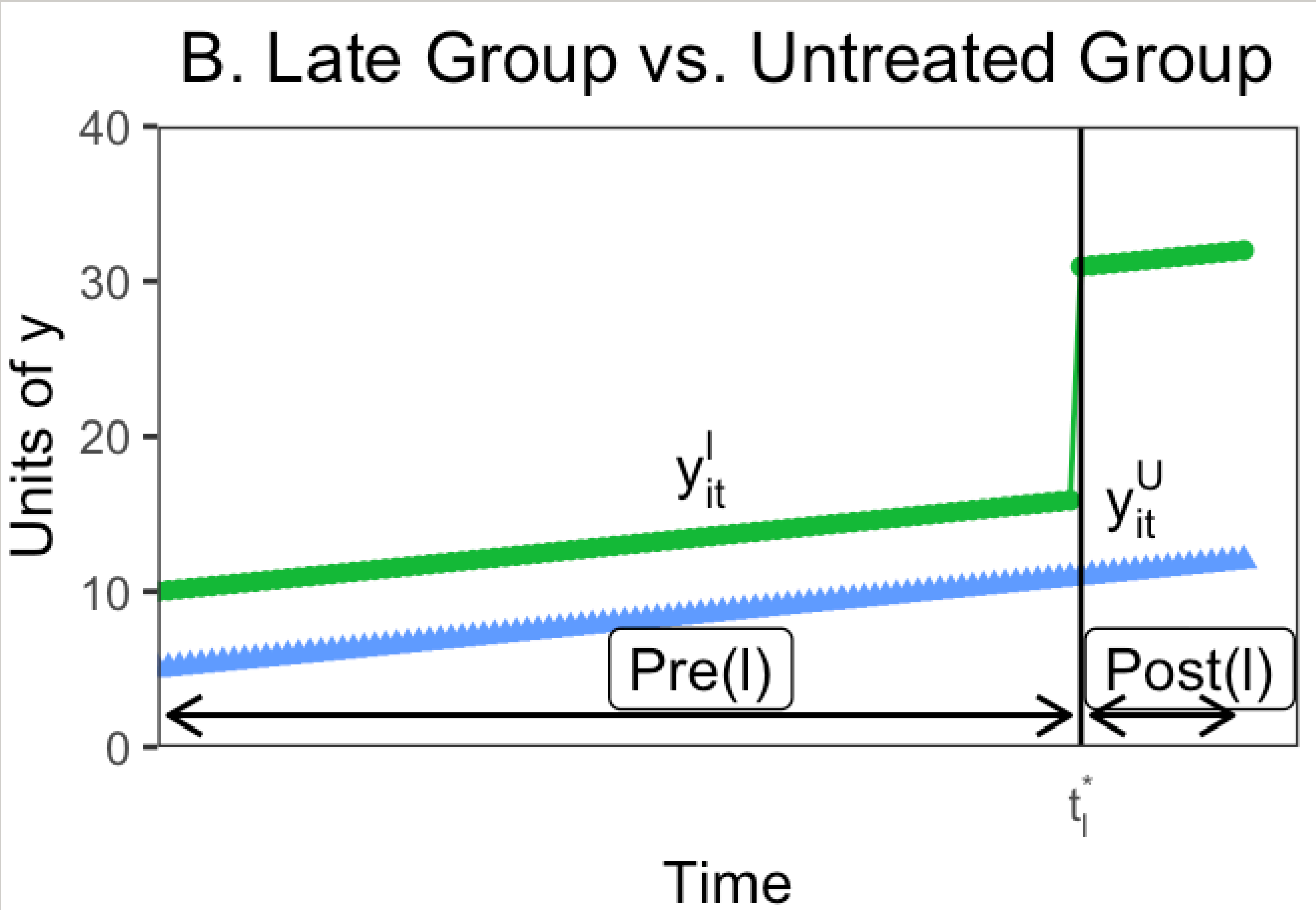


Any design with multiple treatment timings will have k^2 groups, where k is the number of timings.

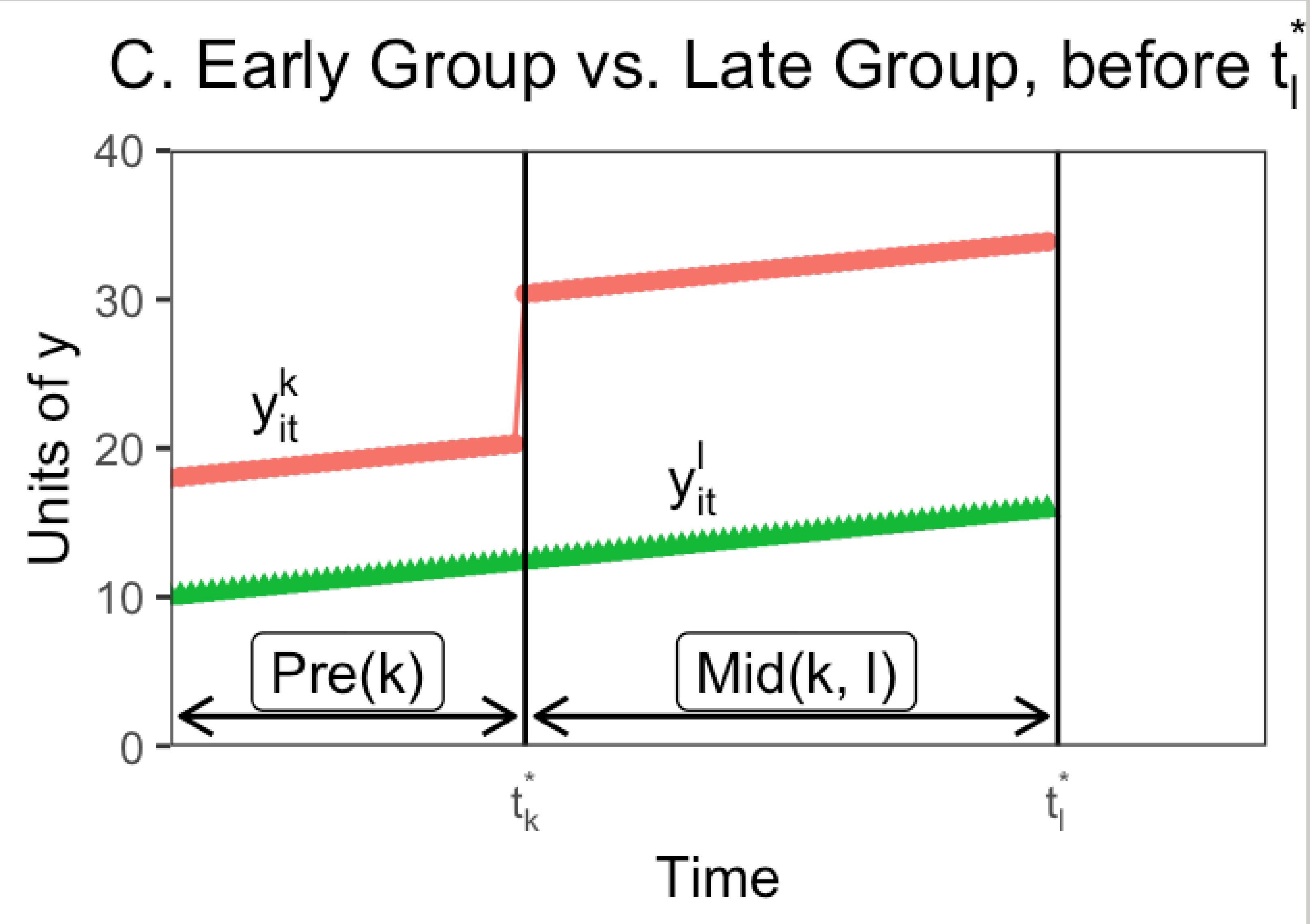
Not a problem



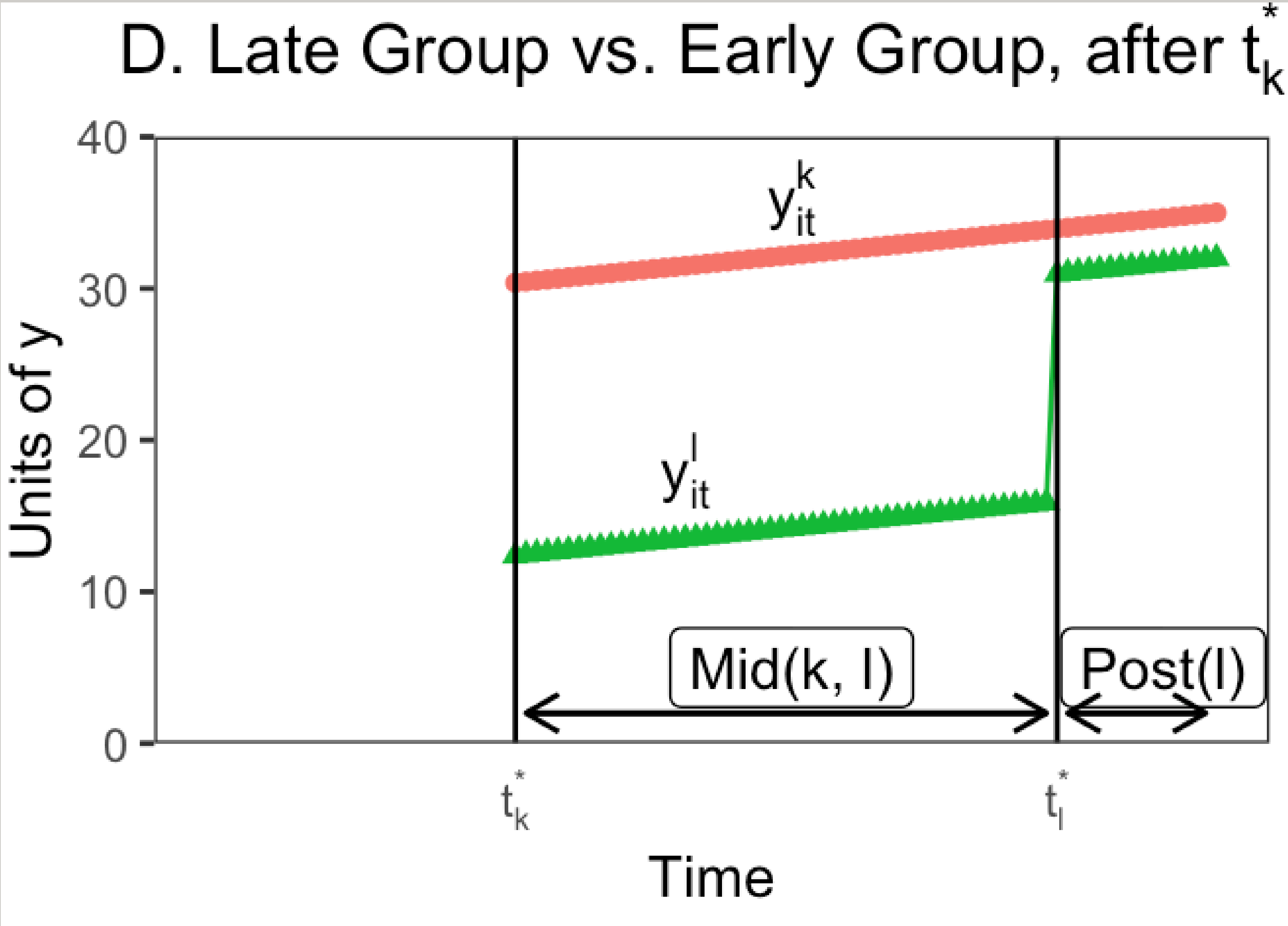
Not a problem



Not a problem



COULD BE PROBLEM!



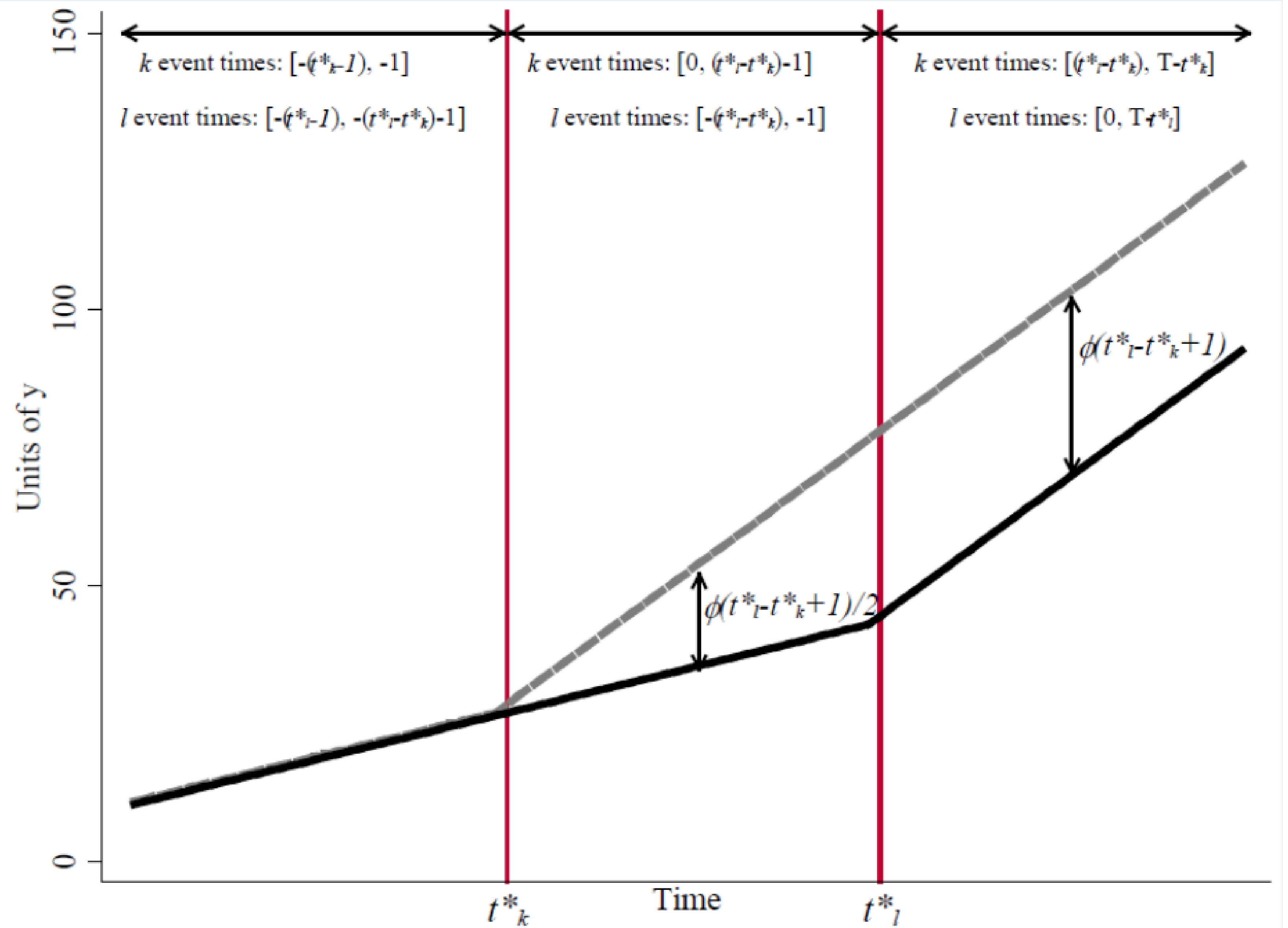
Where does this leave us?

- TWFE treats some data that is under treatment status as comparison!
- Not an issue under constant treatment effect
  - stable unit treatment value (SUTVA)
  - no variation in treatment effect for any reason

But TWFE fails under following conditions:

- different treatment groups have different treatment effects
- treatment effects are dynamic over post-treatment periods
- heterogeneous treatment effects across sub-groups within a treated group

Figure 3. Difference-in-Differences Estimates with Variation in Timing Are Biased When Treatment Effects Vary Over Time



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Adjustment: new estimators

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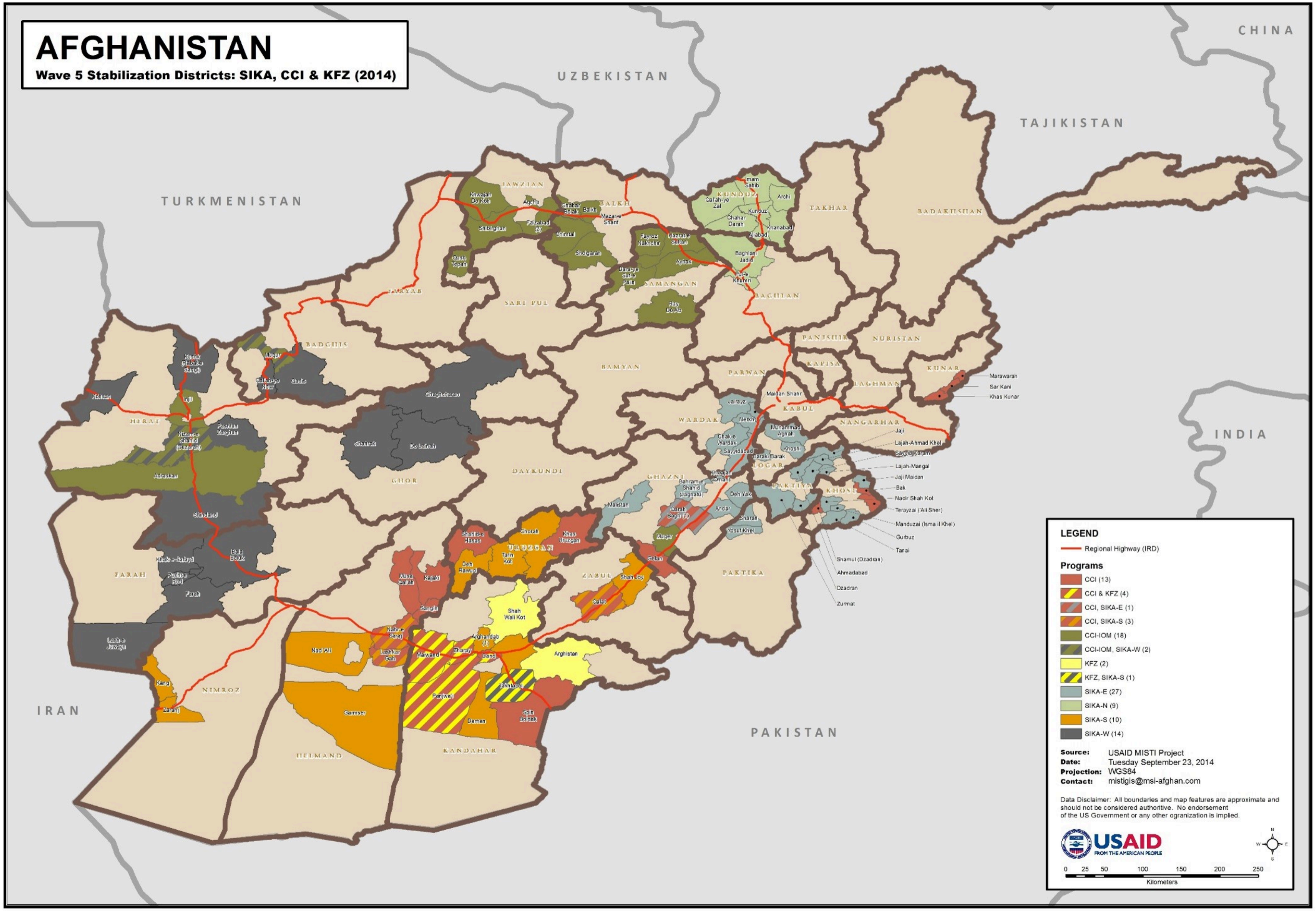
Measuring Impact of Stabilization Initiatives (MISTI)

Can small scale, community-driven development activities build local government legitimacy in a kinetic conflict-affected environment?

MISTI

- Village panel survey in five waves, Sep 2012 - Nov 2014
- ~5,000 villages surveyed across 130 districts and 23 provinces
- ~ 30,000 household interviews per wave
- 860 treated villages at any wave (17%)
- 355 villages surveyed in all five waves
- 85 villages treated (24%)


AFGHANISTAN
Wave 5 Stabilization Districts: SIKA, CCI & KFZ (2014)
UZBEKISTAN
TAJIKISTAN
CHINA
TURKMENISTAN
IRAN
PAKISTAN
INDIA
LEGEND
Regional Highway (IRD)
Programs
CCI (13)
CCI & KFZ (4)
CCI, SIKA-E (1)
CCI, SIKA-S (3)
CCI-IOM (18)
CCI-IOM, SIKA-W (2)
KFZ (2)
KFZ, SIKA-S (1)
SIKA-E (27)
SIKA-N (9)
SIKA-S (10)
SIKA-W (14)
Source: USAID MISTI Project
Date: Tuesday September 23, 2014
Projection: WGS84
Contact: mistigis@msi-afghan.com
Data Disclaimer: All boundaries and map features are approximate and should not be considered authoritive. No endorsement of the US Government or any other organization is implied.
USAID FROM THE AMERICAN PEOPLE
0 25 50 100 150 200 250
Kilometers

MISTI treatment timings

Wave	Comparison villages	Treated villages	Treated villages (cumulative)
1	355	0	0
2	341	14	14
3	322	19	33
4	302	20	53
5	270	32	85

Single-wave analysis

- Final reporting of MISTI relied on a series of single-wave estimations

Measure	Wave 2-4	Wave 2-5	Wave 3-4	Wave 4-5	Wave 3-5
Stability	0.031	0.043	0.003	-0.039	-0.002

MISTI Two Way Fixed Effects (TWFE)

$$y_{it} = \alpha_i + \alpha_t + \beta_{it}^{DD} + \epsilon_{it}$$

$$y_{it} = village_i + wave_t + treated_{it}^{DD} + \epsilon_{it}$$

term	estimate	std.error	statistic	p.value
treat_event	-0.0389	0.0947	-0.411	0.681

Diagnostic: the Bacon decomposition

- The Bacon decomposition will take a TWFE model and decompose it into the full array of 2x2 d-i-d cells used to construct the overall estimate
- The decomposition will also calculate the variance-weights used in regression to see which 2x2 cells are powering the overall estimate
- After diagnosing a problem, the researcher can correct for the bias by using the newer estimators

MISTI bacondecomp

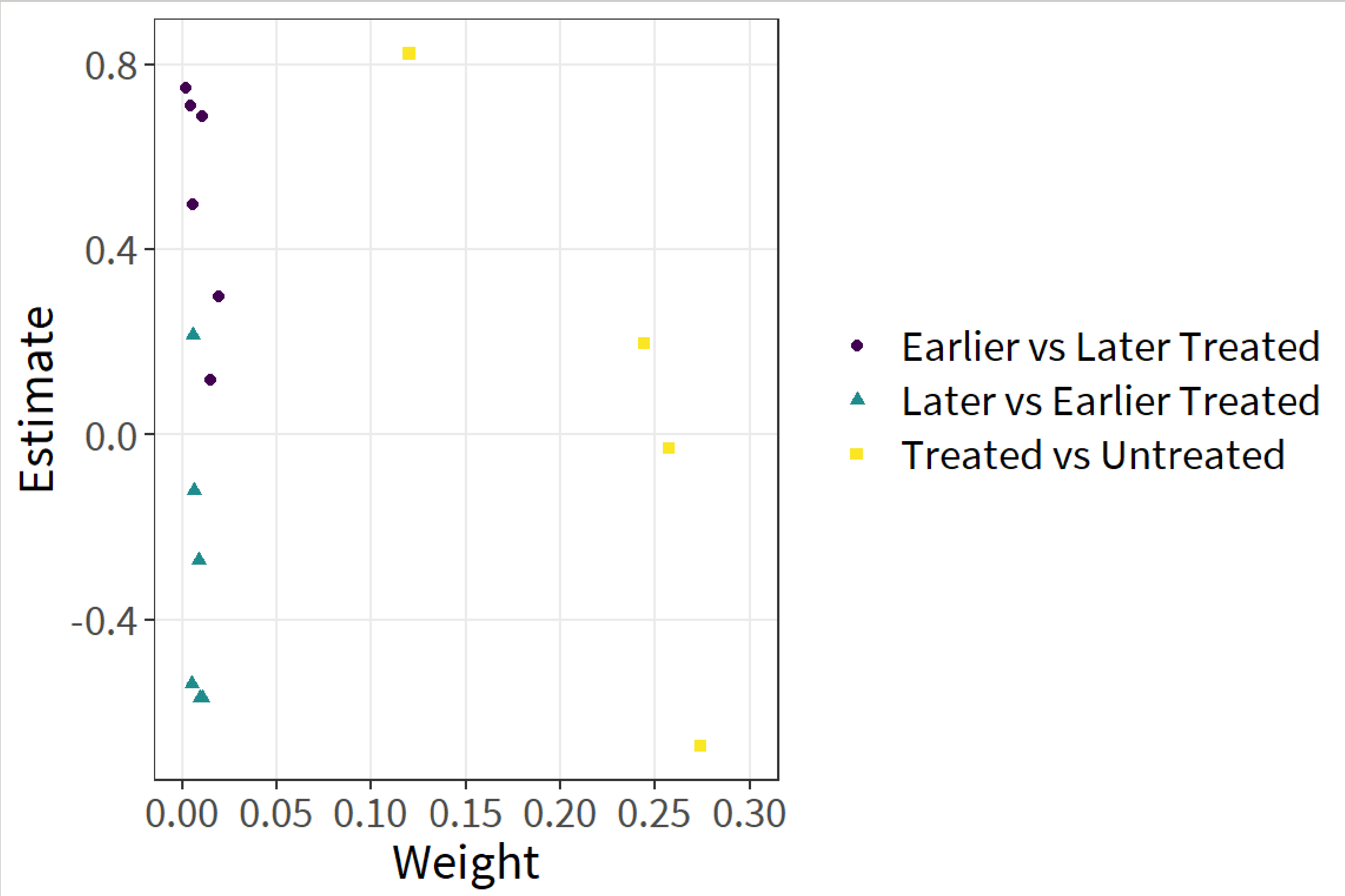
```
                        type weight avg_est
1 Earlier vs Later Treated 0.0578  0.3911
2 Later vs Earlier Treated 0.0466 -0.3465
3     Treated vs Untreated 0.8956 -0.0506
[1] -0.0389
```

term	estimate	std.error	statistic	p.value
treat_event	-0.0389	0.0947	-0.411	0.681

MISTI bacondecomp 2x2 cells

treated	untreated	estimate	weight	type
2	3	0.7473	0.00211	Earlier vs Later Treated
2	4	0.7093	0.00444	Earlier vs Later Treated
2	5	0.6868	0.01066	Earlier vs Later Treated
2	99,999	0.8232	0.11998	Treated vs Untreated
3	2	-0.1216	0.00633	Later vs Earlier Treated
3	4	0.4973	0.00603	Earlier vs Later Treated
3	5	0.2976	0.01930	Earlier vs Later Treated
3	99,999	0.1964	0.24425	Treated vs Untreated
4	2	-0.2707	0.00889	Later vs Earlier Treated
4	3	0.2135	0.00603	Later vs Earlier Treated
4	5	0.1182	0.01524	Earlier vs Later Treated
4	99,999	-0.0291	0.25710	Treated vs Untreated
5	2	-0.5680	0.01066	Later vs Earlier Treated
5	3	-0.5686	0.00965	Later vs Earlier Treated
5	4	-0.5375	0.00508	Later vs Earlier Treated
5	99,999	-0.6729	0.27424	Treated vs Untreated

Plot of 2x2 cells

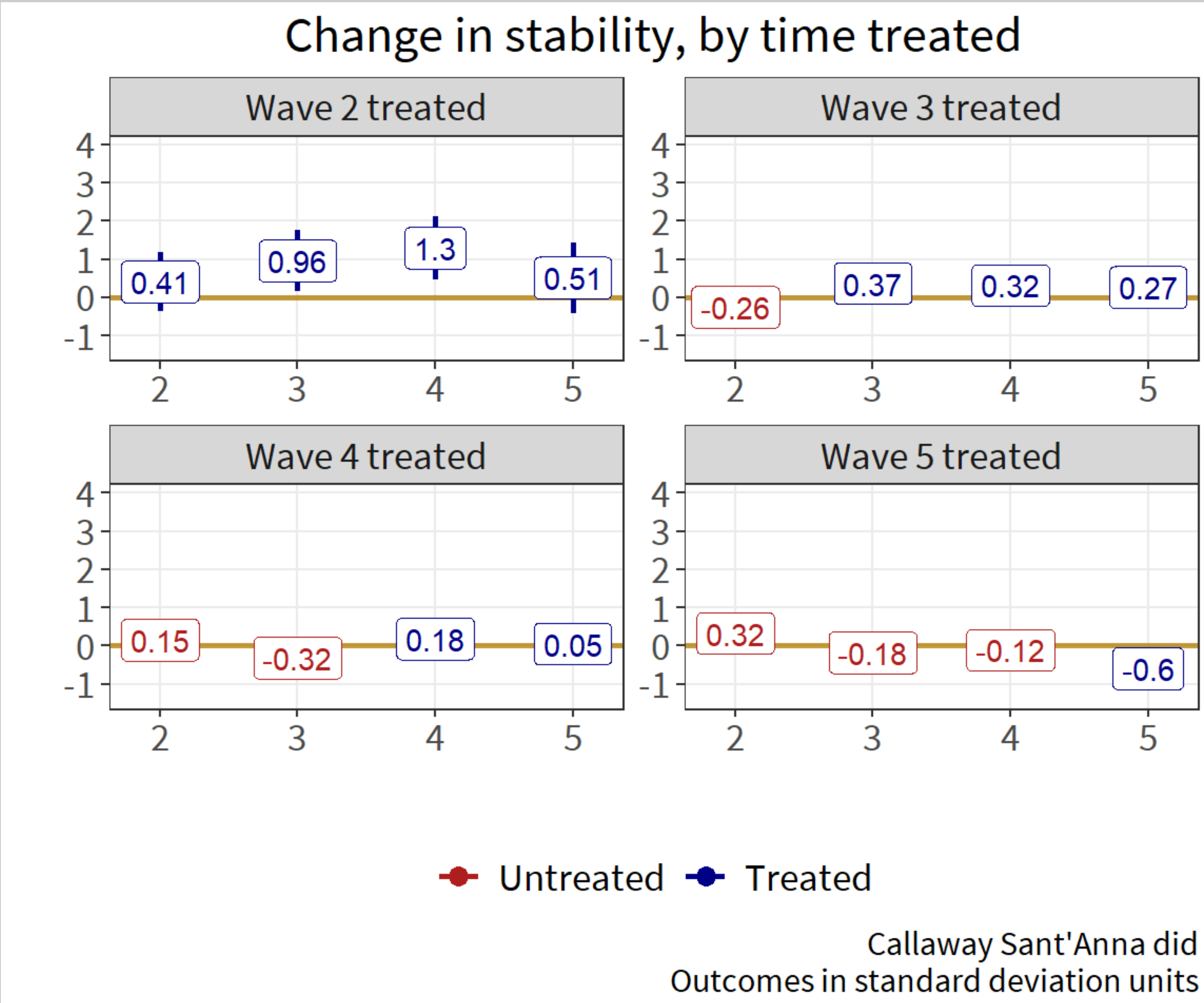


Callaway and Sant'Anna (2020)

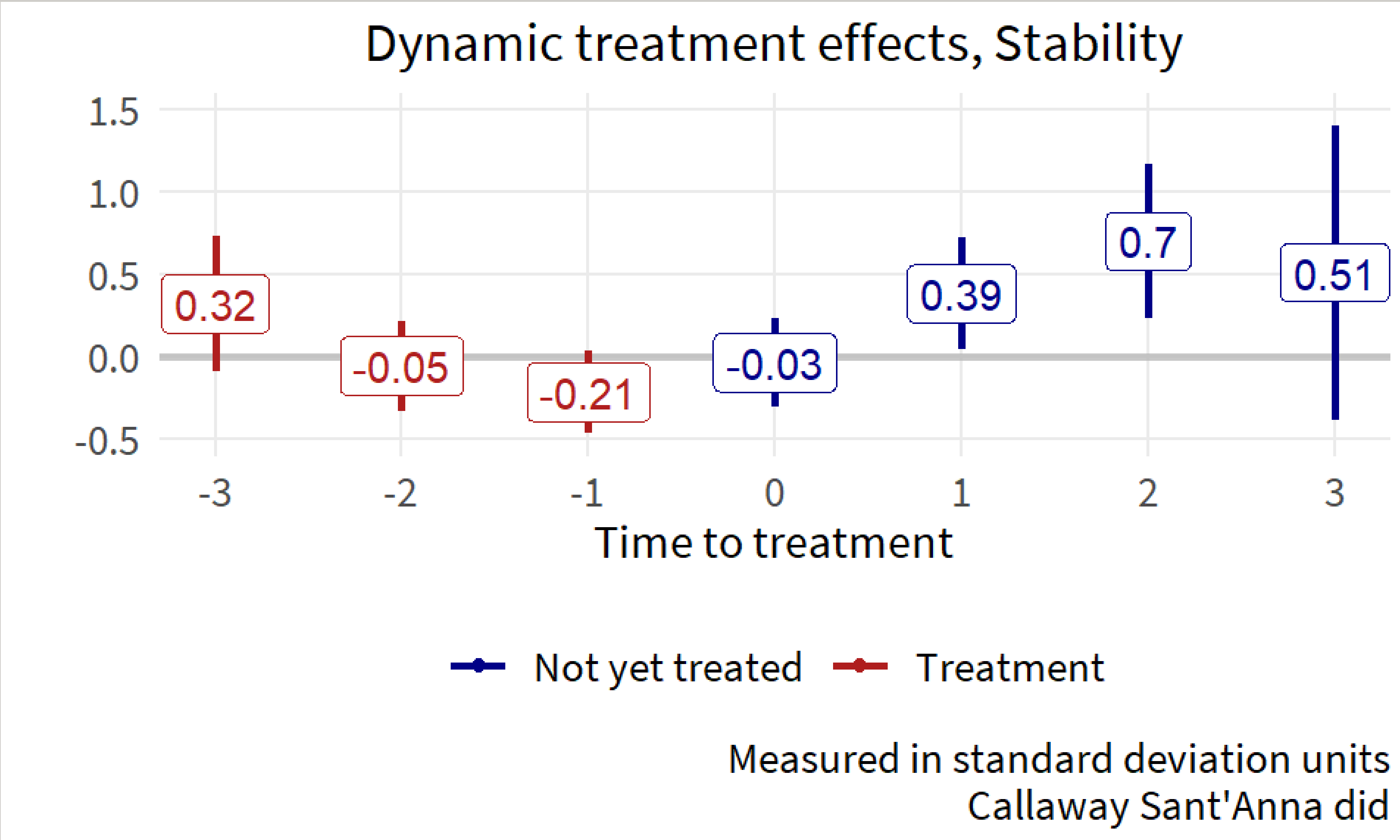
This estimation gives you multiple outcomes

- Treatment by treatment group
- An overall treatment effect
- Overall dynamic effects / event study

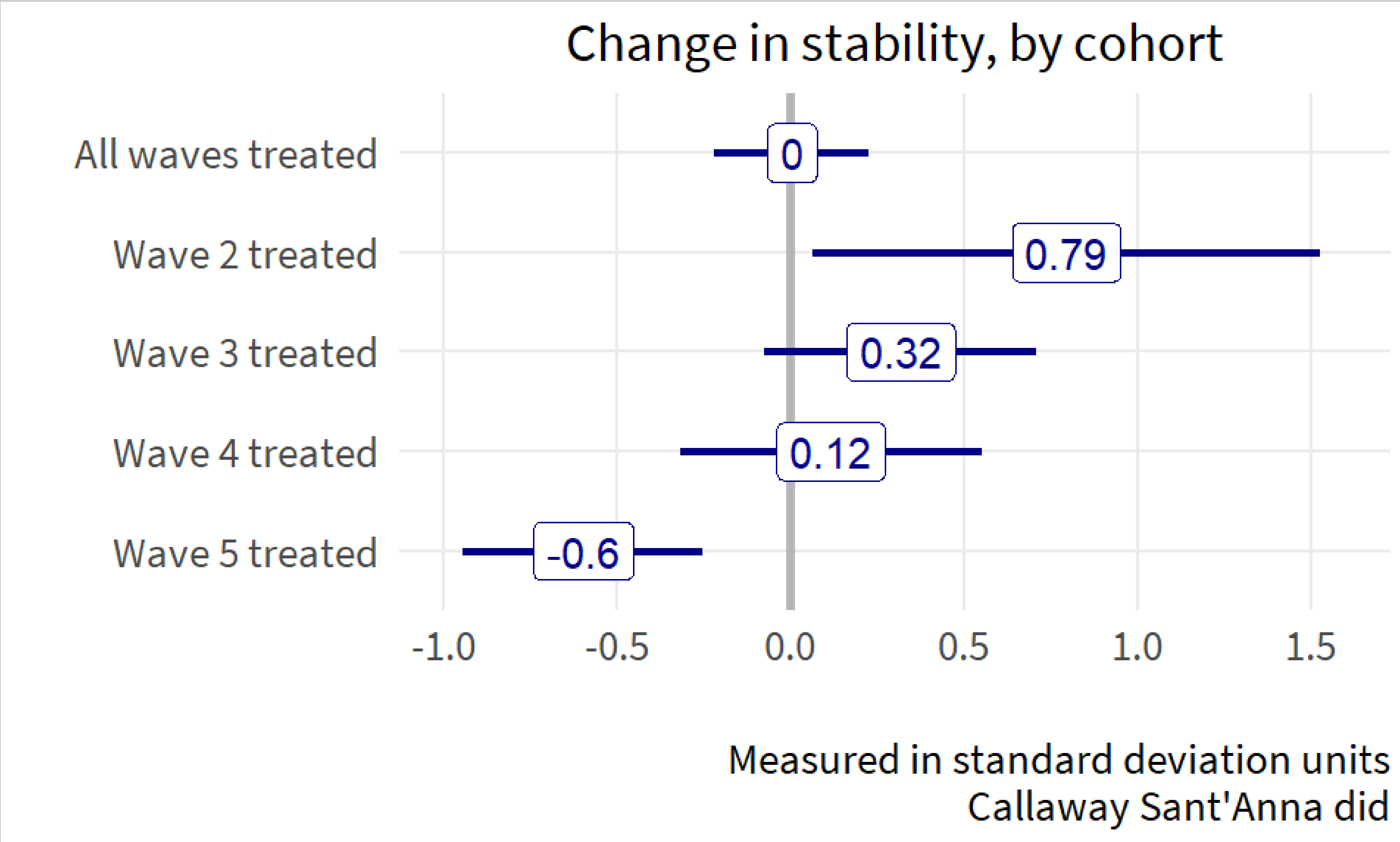
Treatment effects for each wave



Dynamic treatment effects



Overall effects by cohort



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What have we learned?

- In certain settings, two-way fixed effects estimation is biased in ways that we only recently came to realize
- We have to carefully think through the data generating process (logic modeling) for each individual setting
- As we get more granular data and ask deeper questions, econometric tools are starting to provide better insight into treatment dynamics

What should we do?

- For any two-way fixed effects setting, use the Bacon decomposition to diagnose any problems
- Use event study designs to examine dynamic treatment effects
- Re-examine old evaluations!!

Thank you!