

Rescuing impact measurements

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

2024-09-06

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?

where..

β_0 is the comparison group at baseline

β_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

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

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

Generalizing d-i-d to multiple periods or 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

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

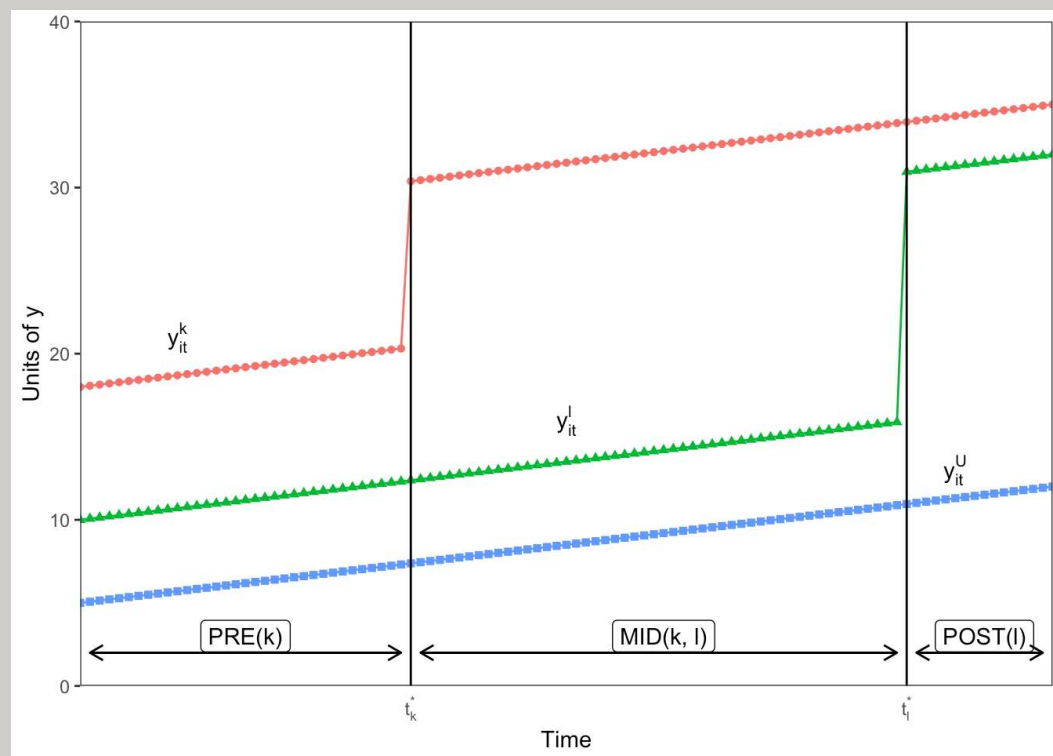
β_{it}^{DD}

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

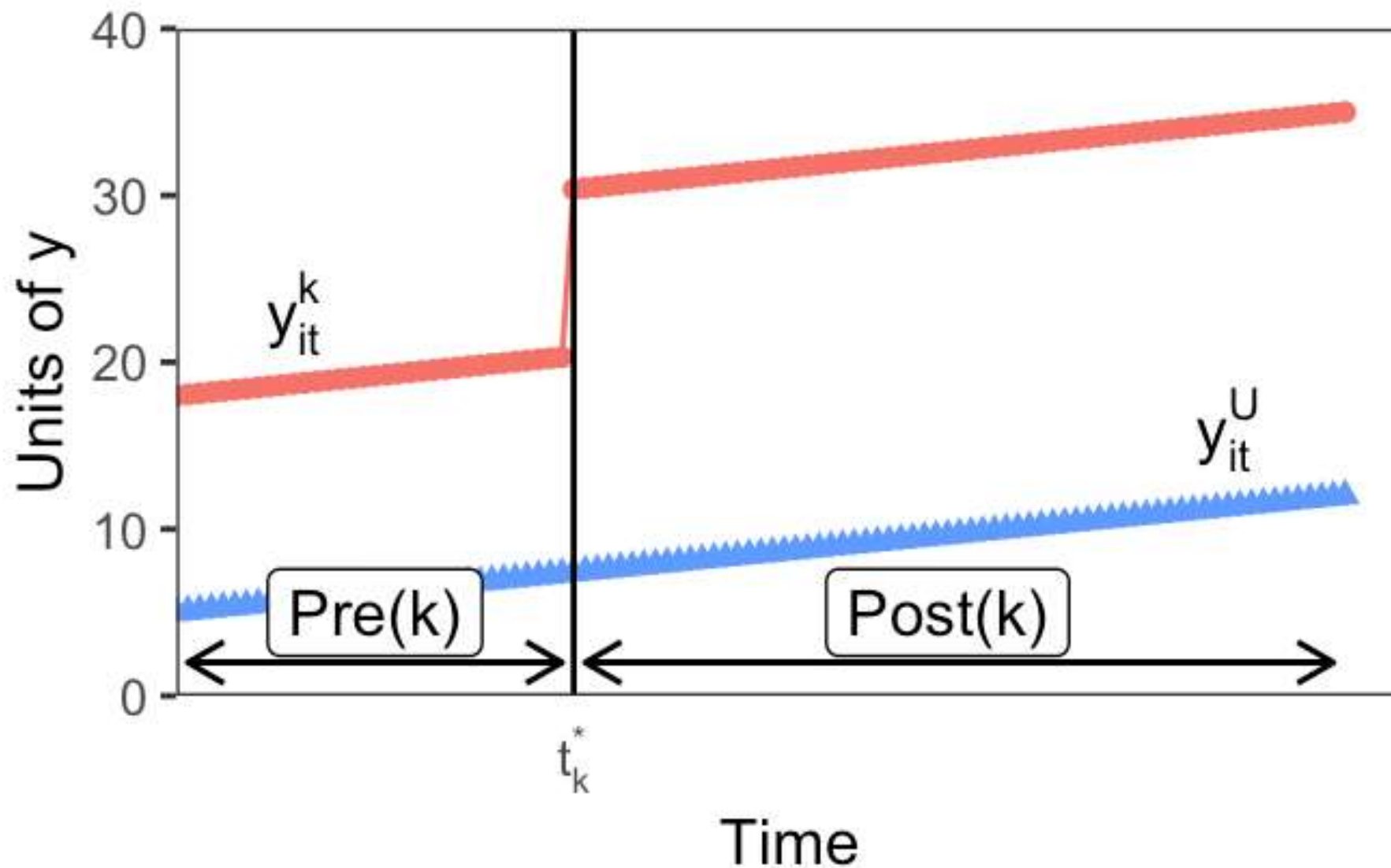
- For the canonical 2×2 , we know exactly what we are estimating
- For i groups and t time periods, we are getting some average of multiple 2×2 s
- But how does this work, exactly?

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

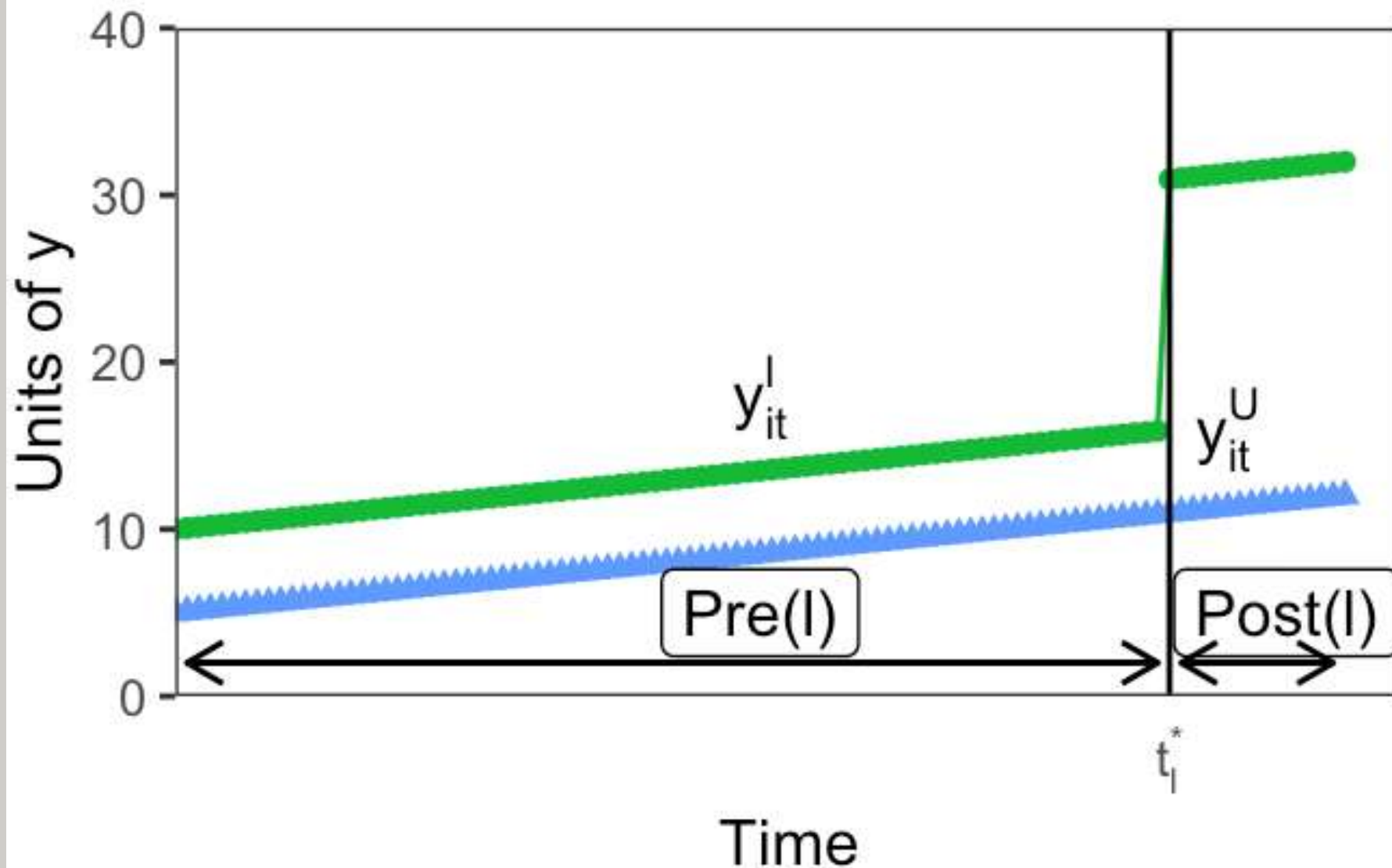


Any design with multiple treatment timings will have k^2 groups, where k is the number of timings.

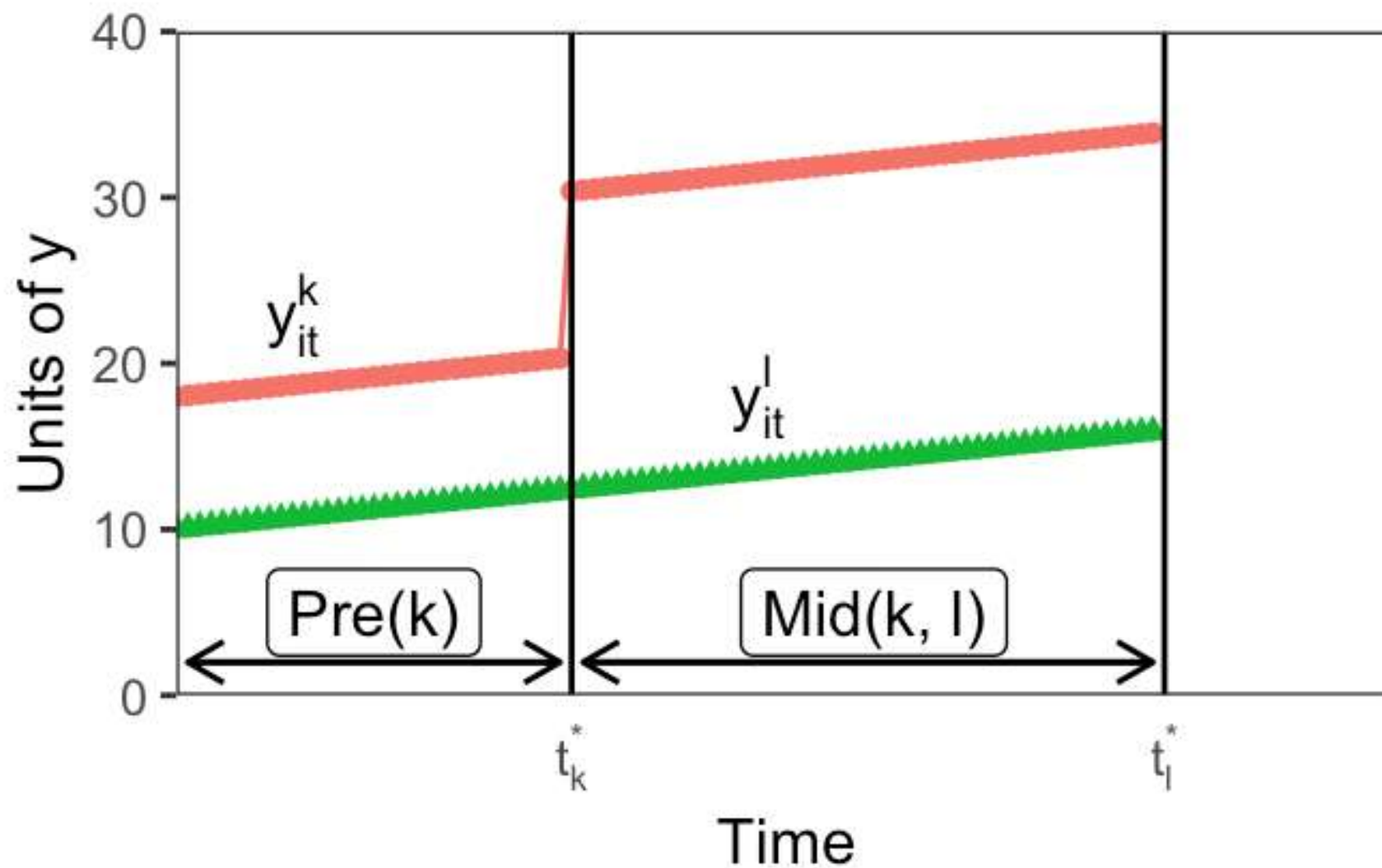
A. Early Group vs. Untreated Group



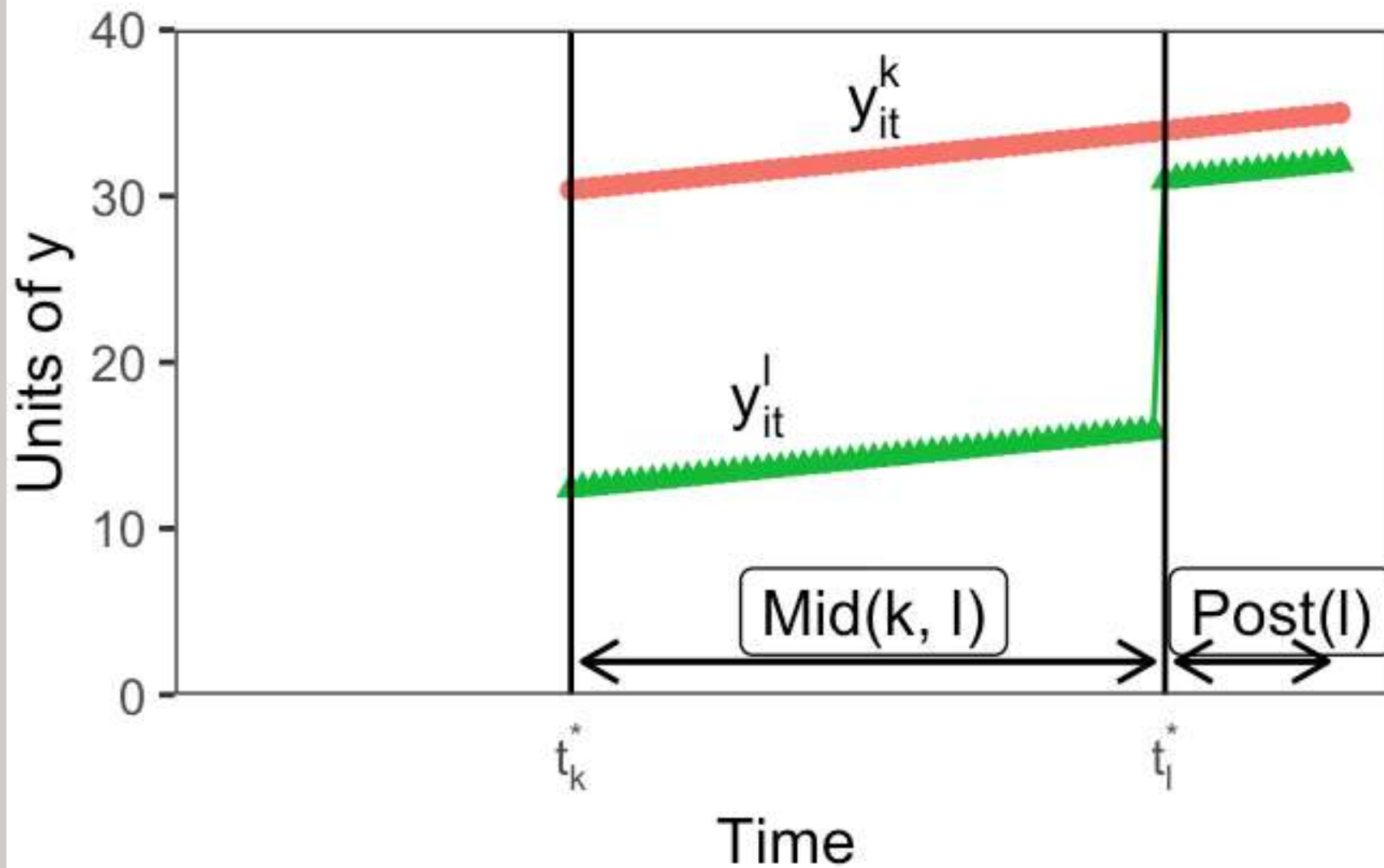
B. Late Group vs. Untreated Group



C. Early Group vs. Late Group, before t_l^*



D. Late Group vs. Early Group, after t_k^*



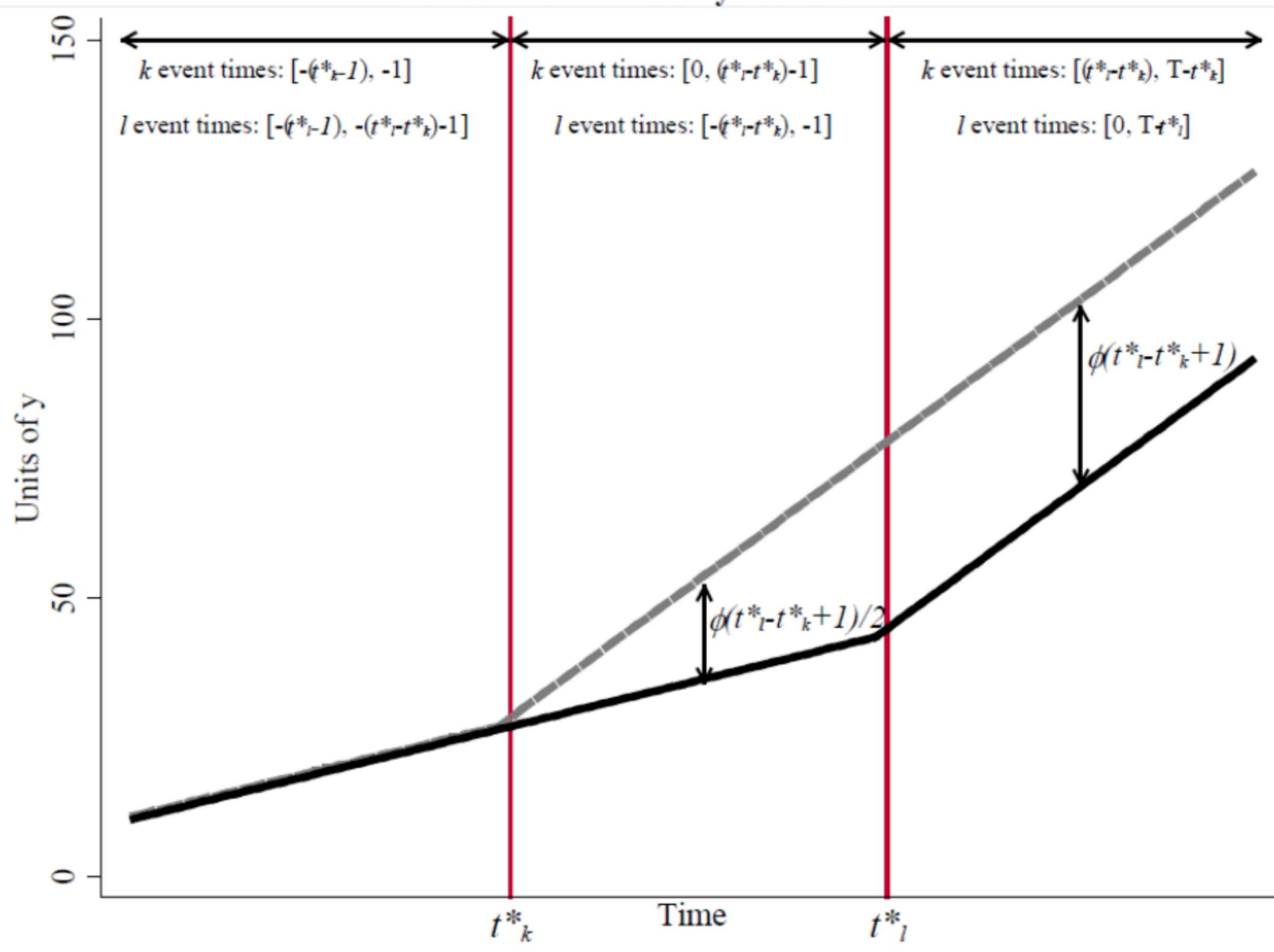
Where does this leave us?

- 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)

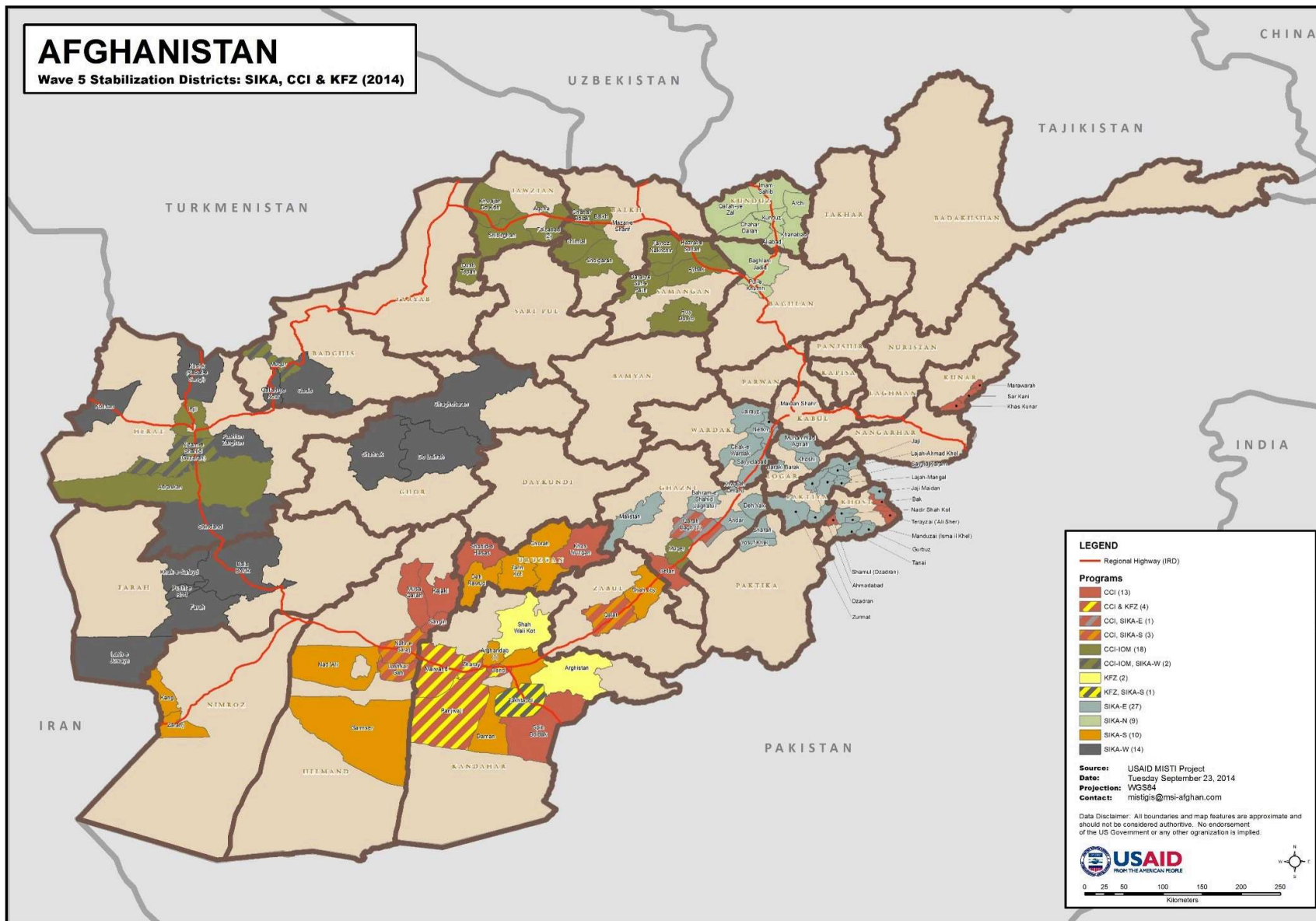
Can small scale, community-driven development activities build local government legitimacy in a kinetic conflict-affected environment?

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)



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)

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

$$y_{it} = \text{village}_i + \text{wave}_t + \text{treated}_{it}^{DD} + \epsilon_{it}$$

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 bacondcomp

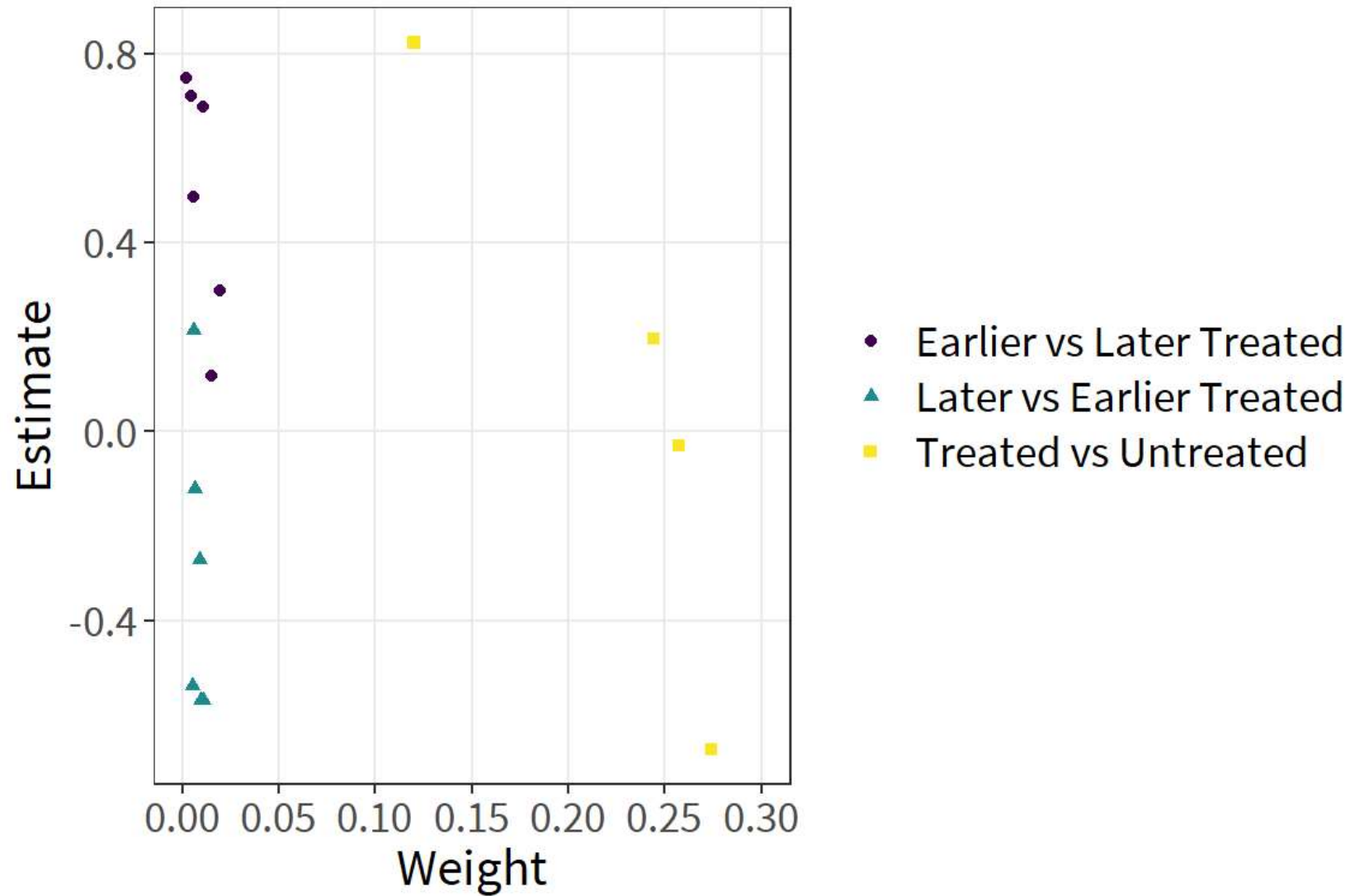
	type	weight	avg_est
1	Earlier vs Later Treated	0.0578	0.3911
2	Later vs Earlier Treated	0.0466	-0.3465
3	Treated vs Untreated	0.8956	-0.0506

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

[1] -0.0389

Plot of 2x2 cells

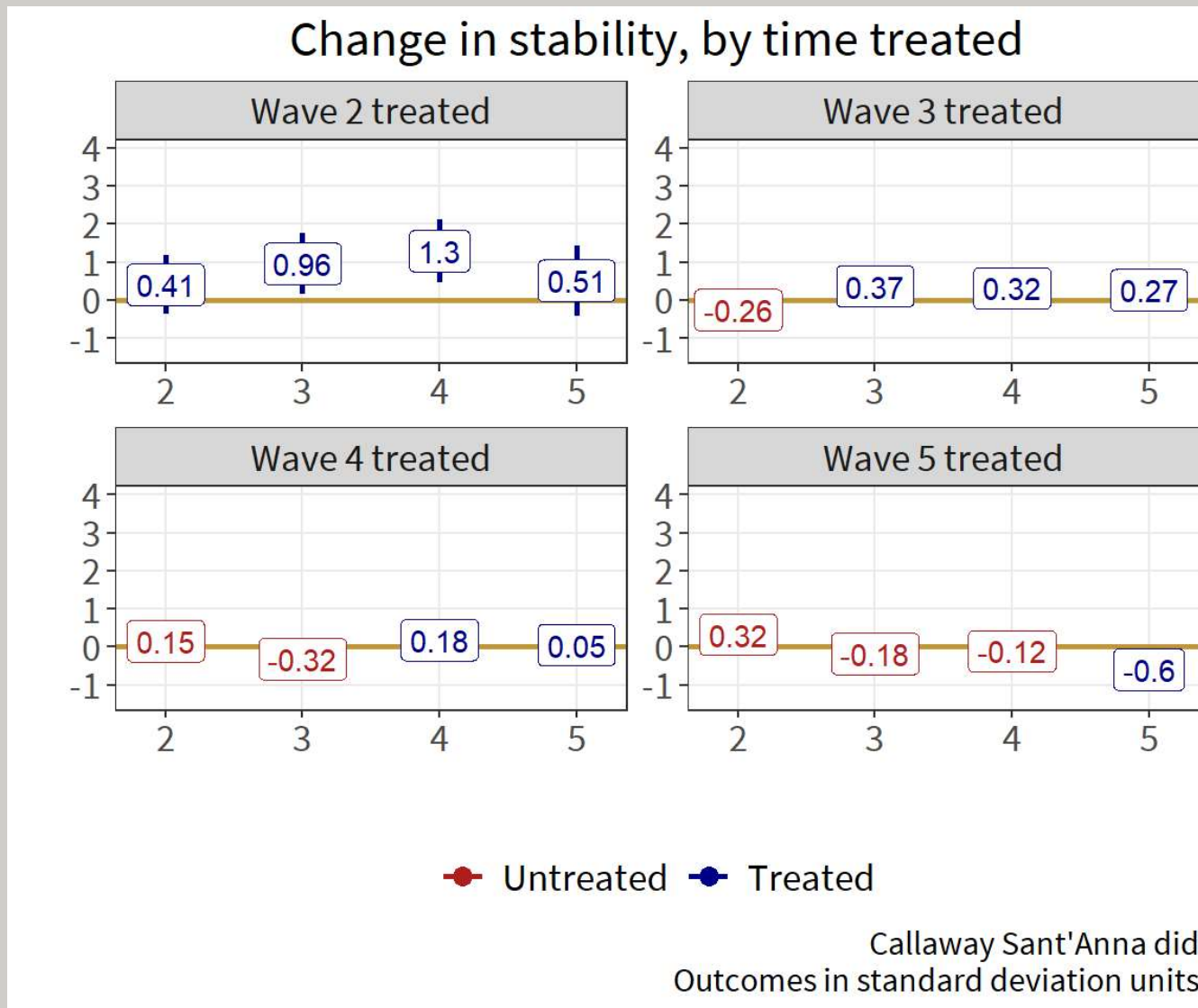


Callaway and Sant'Anna (2020)

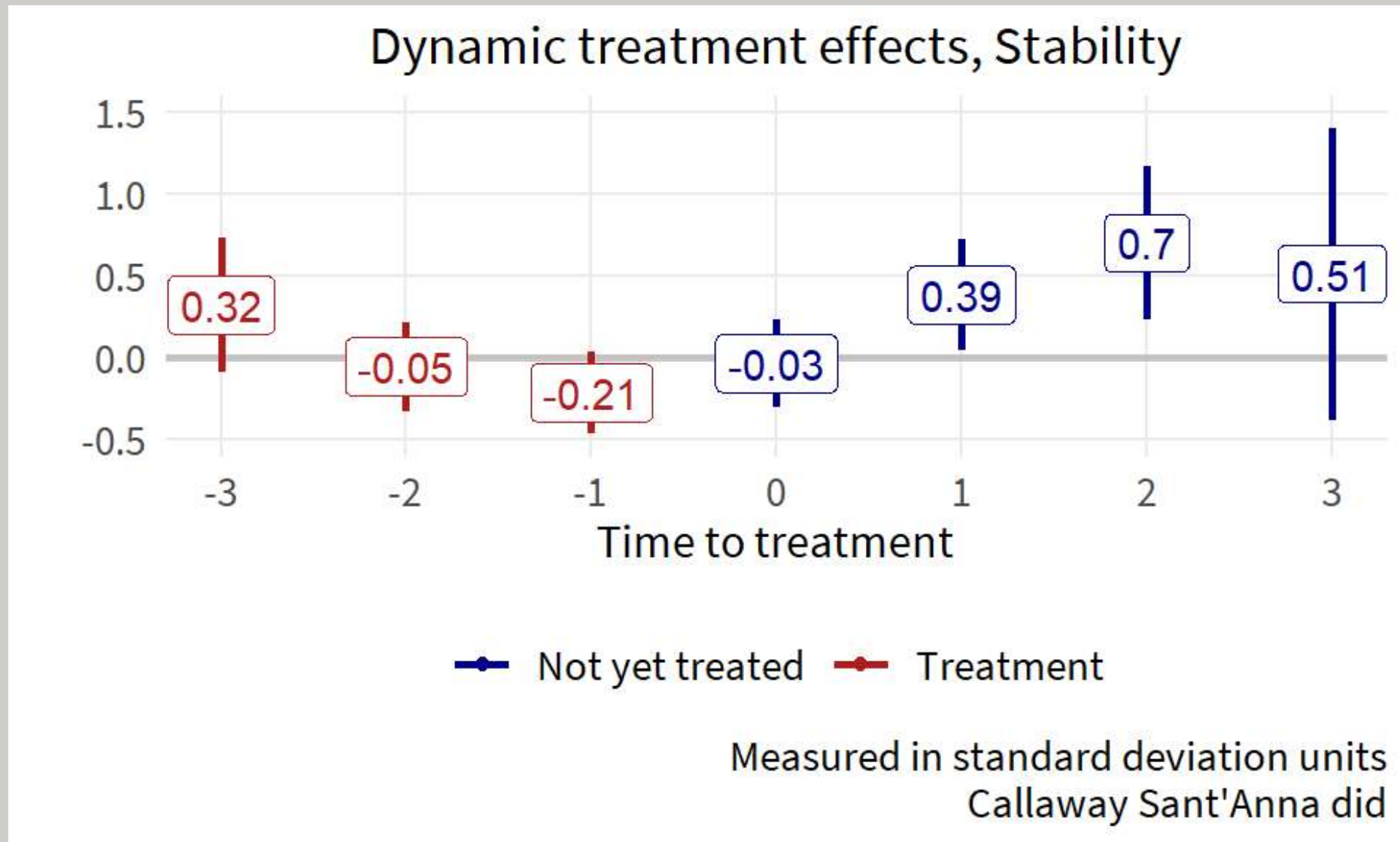
This estimation gives you multiple outcomes

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

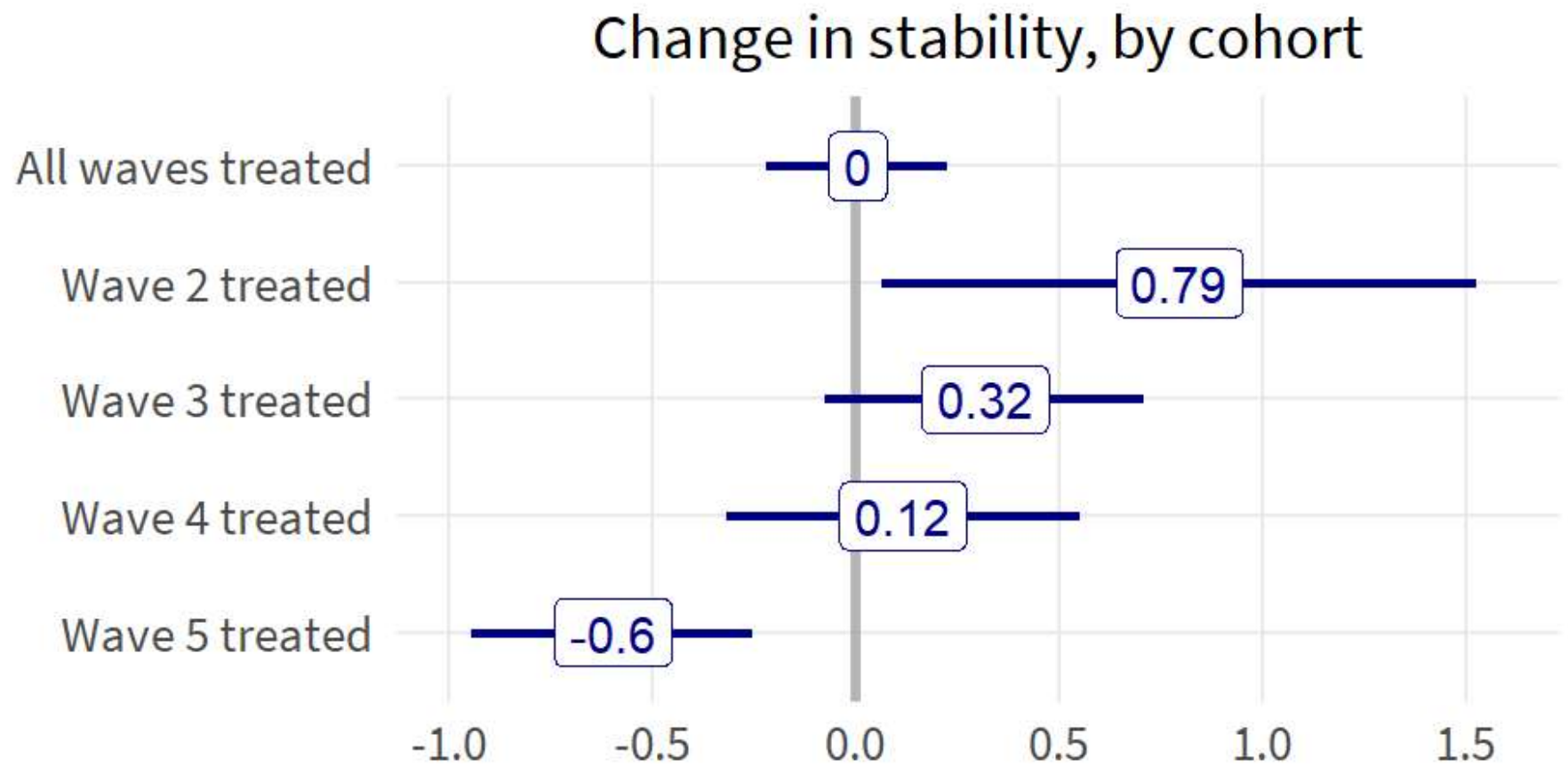
Treatment effects for each wave



Dynamic treatment effects



Overall effects by cohort



Measured in standard deviation units
Callaway Sant'Anna did

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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!