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Rescuing impact measurements

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

Session Objectives

- Understand the basic setup of quasi-experimental difference-in-differences
- Understand how d-i-d generalizes to multiple time periods and groups, and how complications can arise
- Recognize adjustments to handle additional complexity
- Appreciate that generating defensible quasi-experimental impact estimates is difficult

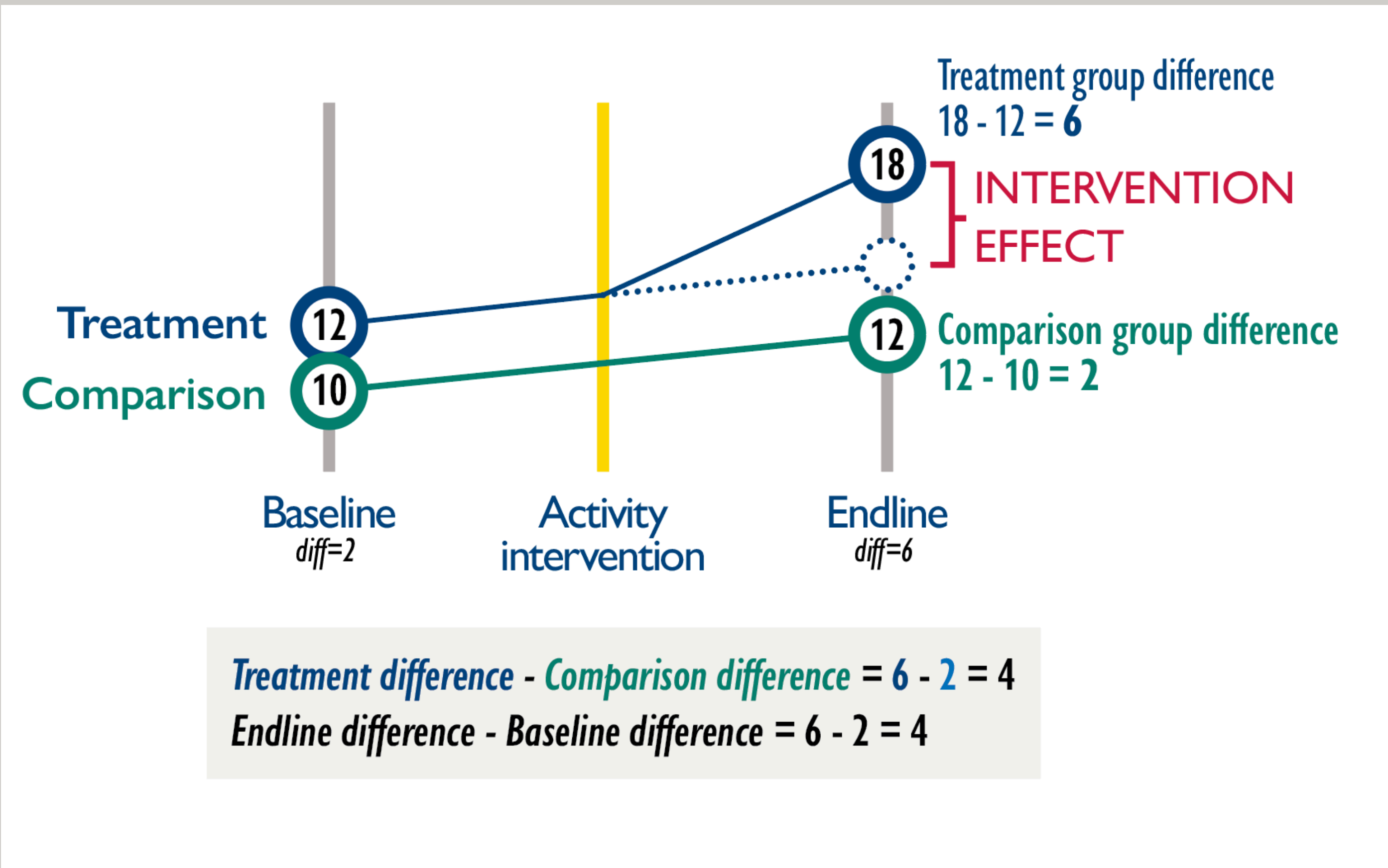
How Do We Do Difference-in-differences?

- Under randomized d-i-d, the pre-treatment measurement is used to improve precision
- Under quasi-experimental d-i-d, we depend on the pre-treatment trend to remove time-invariant sources of bias
- For this to work, we must demonstrate or convincingly argue for parallel pre-treatment trends
- If we justify parallel trends, we can use the break in trends after treatment to estimate the treatment effect

Quasi-experimental d-i-d

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

$$y_{it} = 10 + 2 \times Post_t + 2 \times Treat_i + 4 \times Post_t \times Treat_i + \epsilon_{it}$$



The Estimating Equation

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

where..

β_0 is the comparison group at baseline

δ_0 is the change in comparison group from baseline to endline

β_1 is the baseline difference between the treatment and comparison

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

Plugging Values into the Equation

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

$$y_{it} = 10 + 2 \times Post_t + 2 \times Treat_i + 4 \times Post_t \times Treat_i + \epsilon_{it}$$

Group	Baseline	Endline	Difference
Comparison	10	12	2
	β_0	$\beta_0 + \delta_0$	δ_0
Treatment	12	18	6
	$\beta_0 + \beta_1$	$\beta_0 + \delta_0 + \beta_1 + \delta_1$	$\delta_0 + \delta_1$
Difference	2	6	4
	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

$$y_{gt} = \alpha_g + \alpha_t + \beta_{gt}^{DD} + \epsilon_{gt}$$

where..

α_g are group fixed effects

α_t are time fixed effects

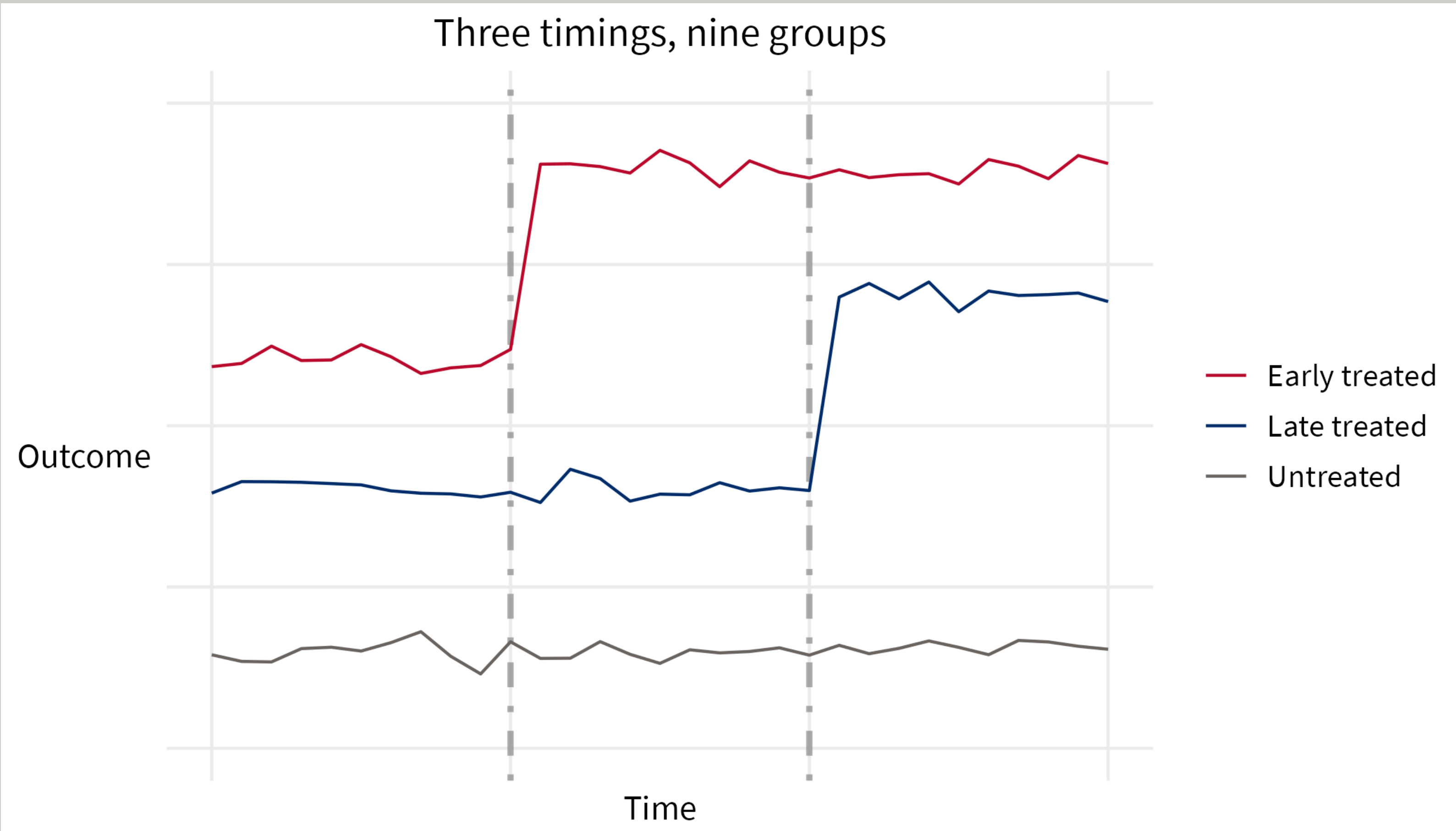
B_{gt}^{DD} indicates whether group g in period *t* is treated

But What is β_{gt}^{DD} Actually Telling Us?

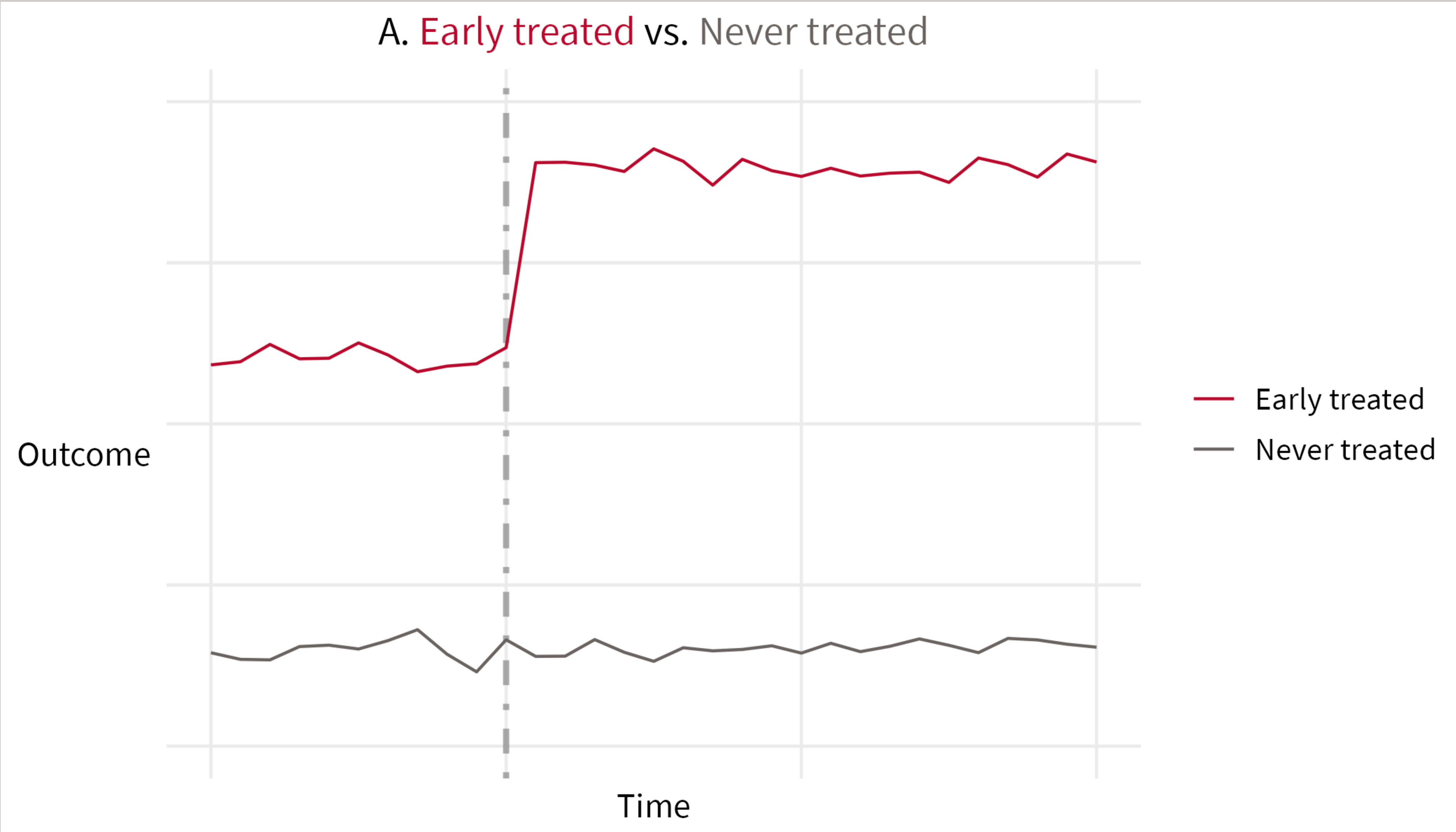
- For the canonical 2x2, we know exactly what we are estimating
- For *g* groups and *t* time periods, we are getting some average of multiple 2x2s
- But how does this work, exactly?

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



Not a Problem



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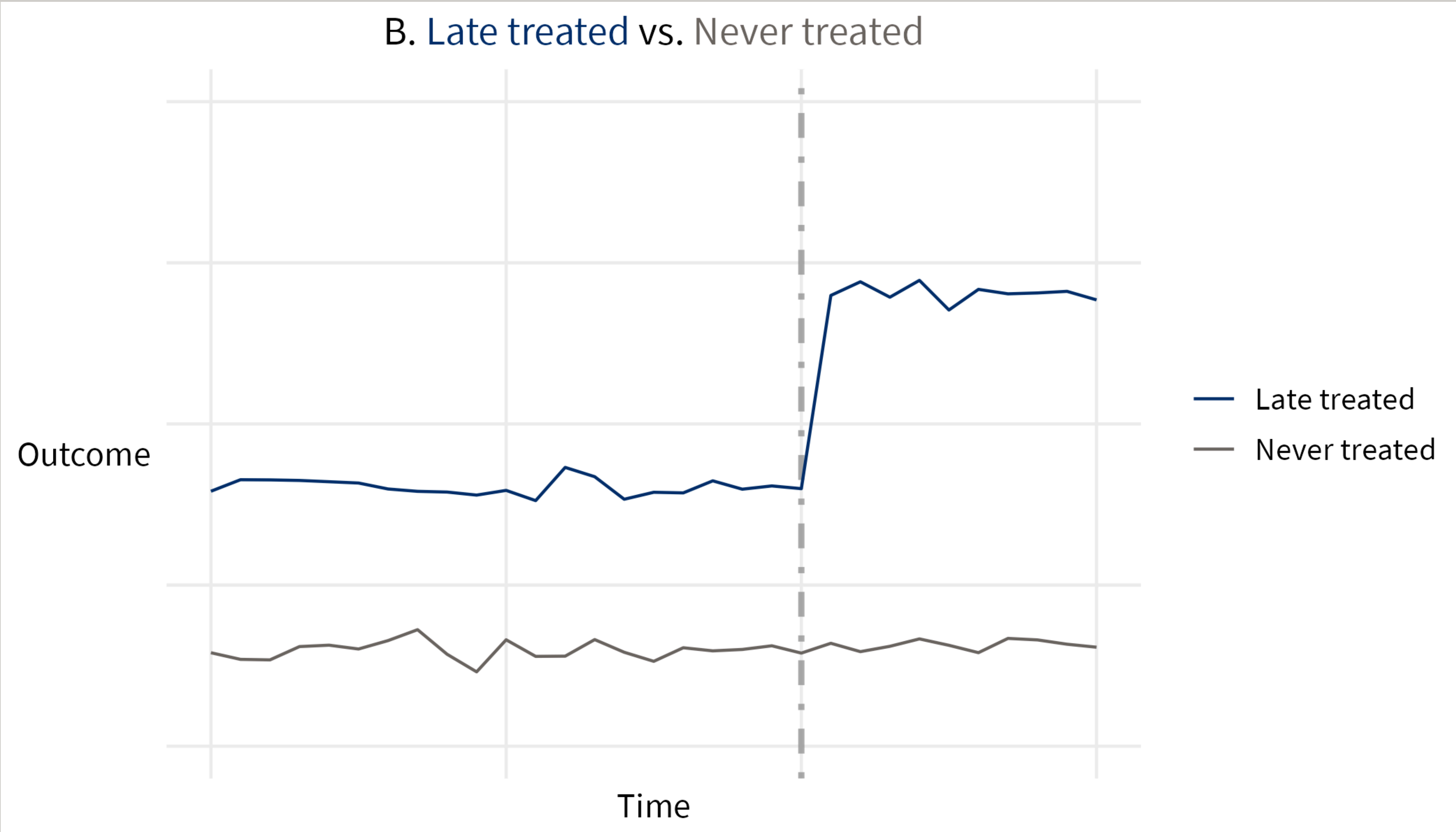
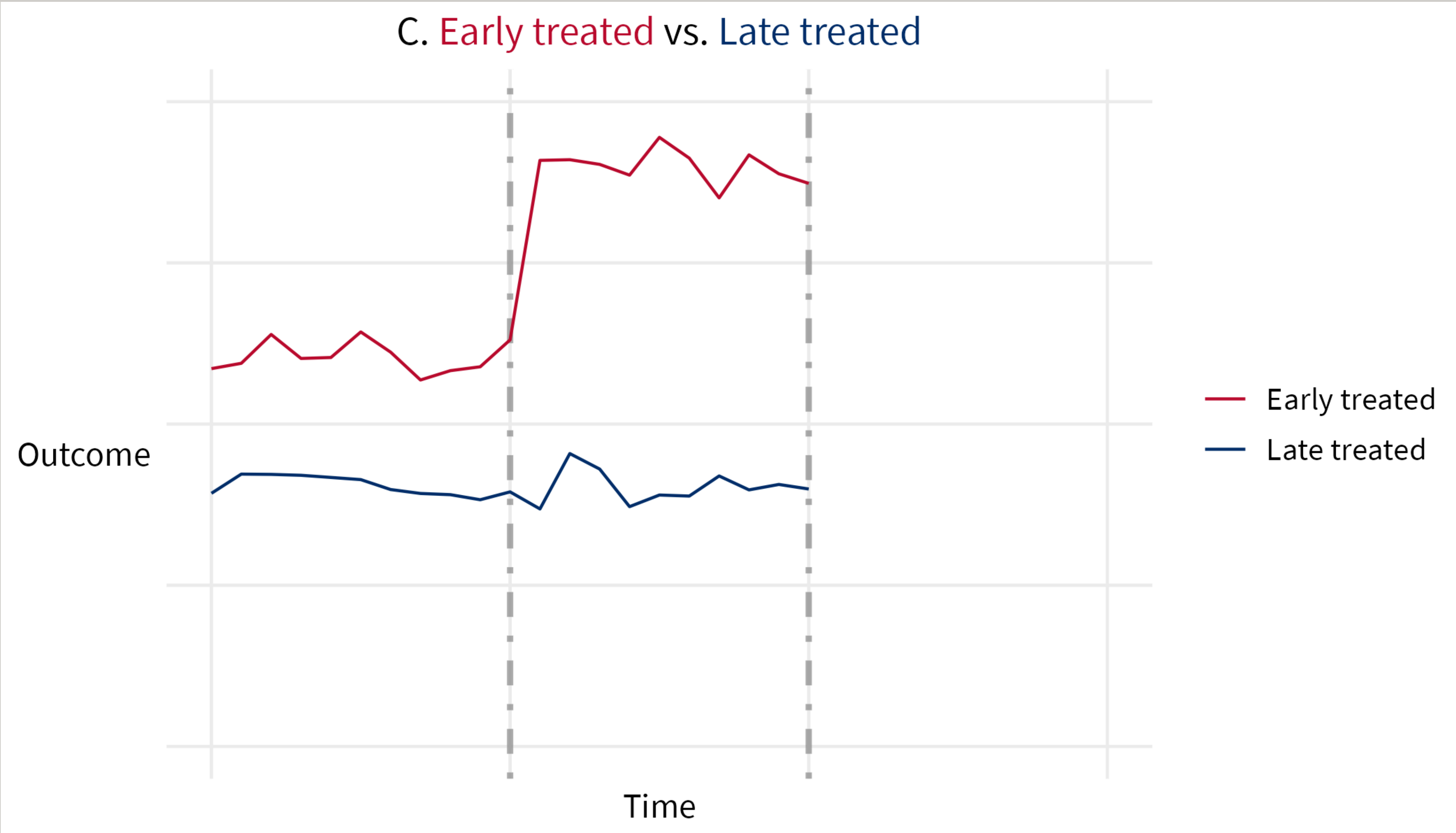
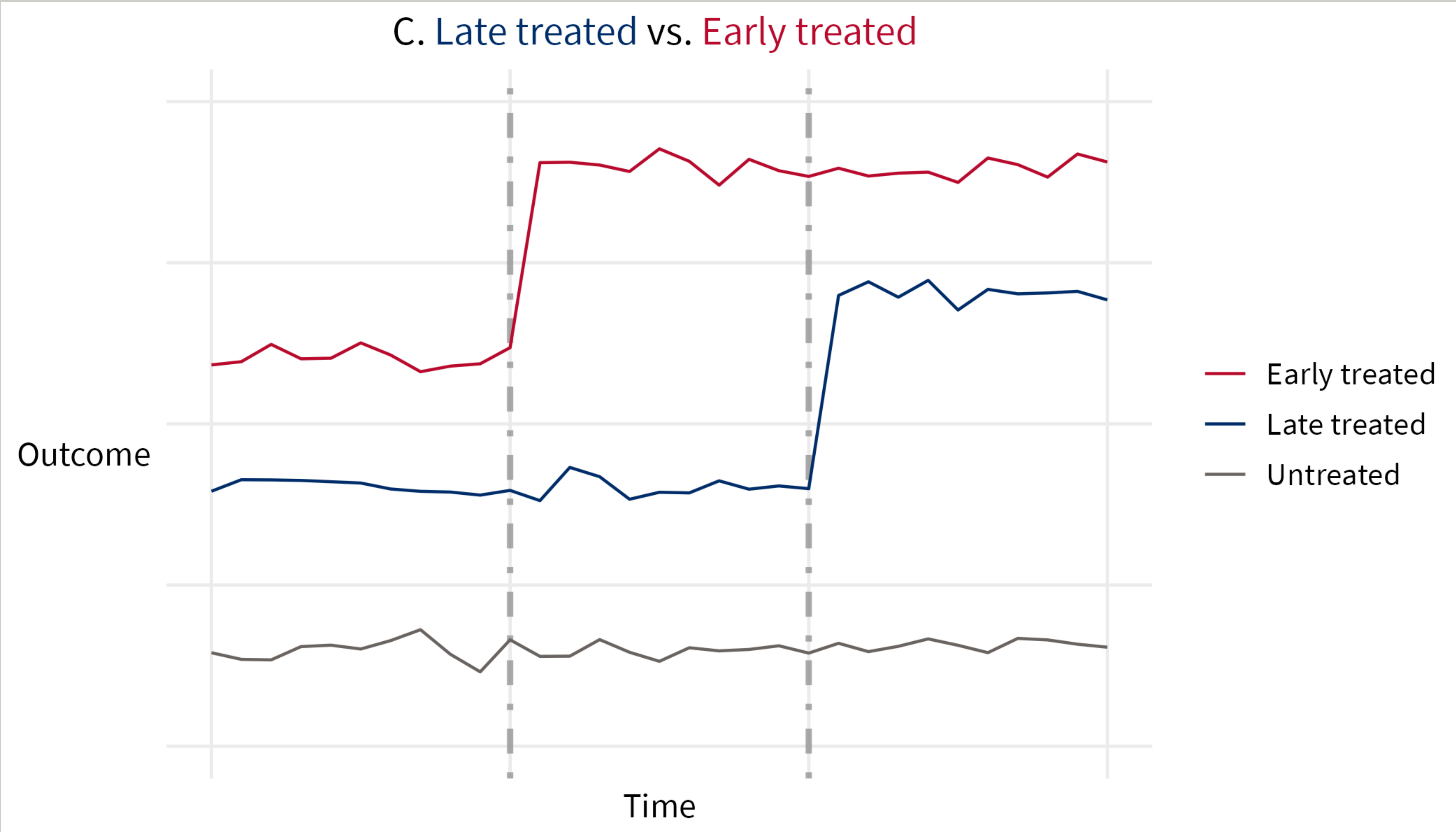


Not a Problem



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

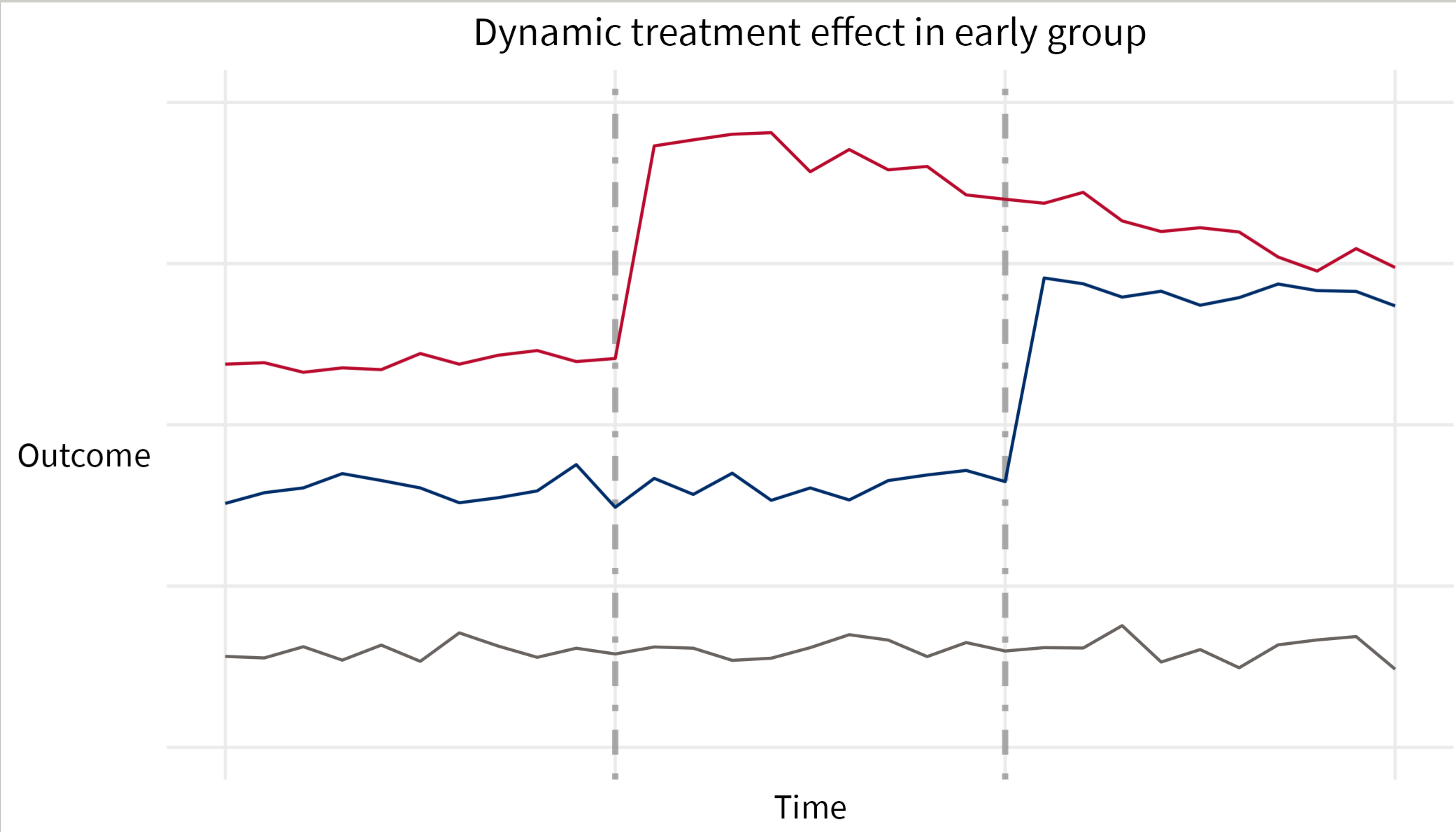
TWFE Fails

But TWFE fails under the 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

Definitely a Problem

What is the solution?



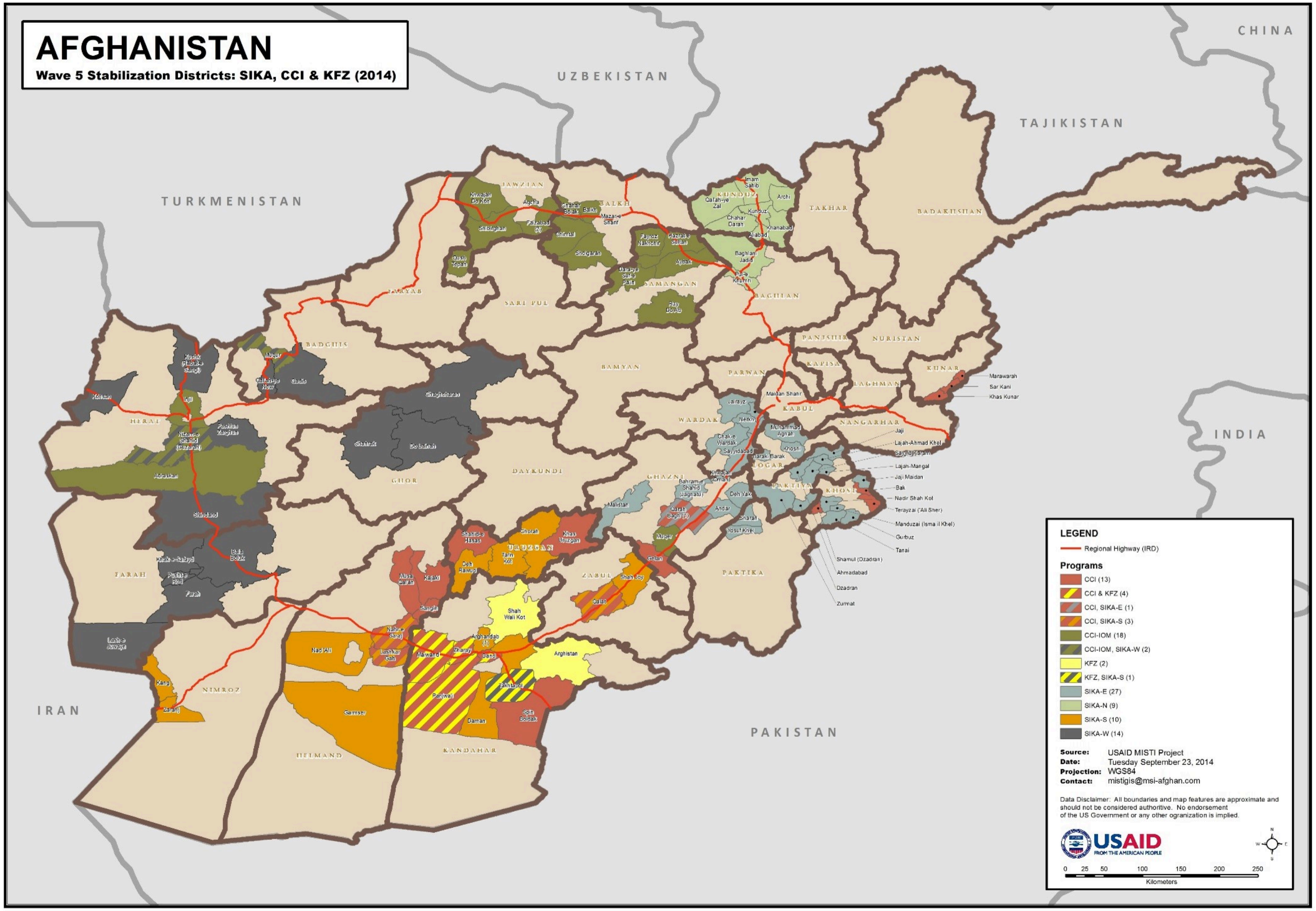
New Estimators, Old Evaluation

- Measuring Impact of Stabilization Initiatives (MISTI)
- Can community-driven development activities build local government legitimacy in a conflict-affected environment?

MISTI Background

- 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%)

MISTI Treatment Areas



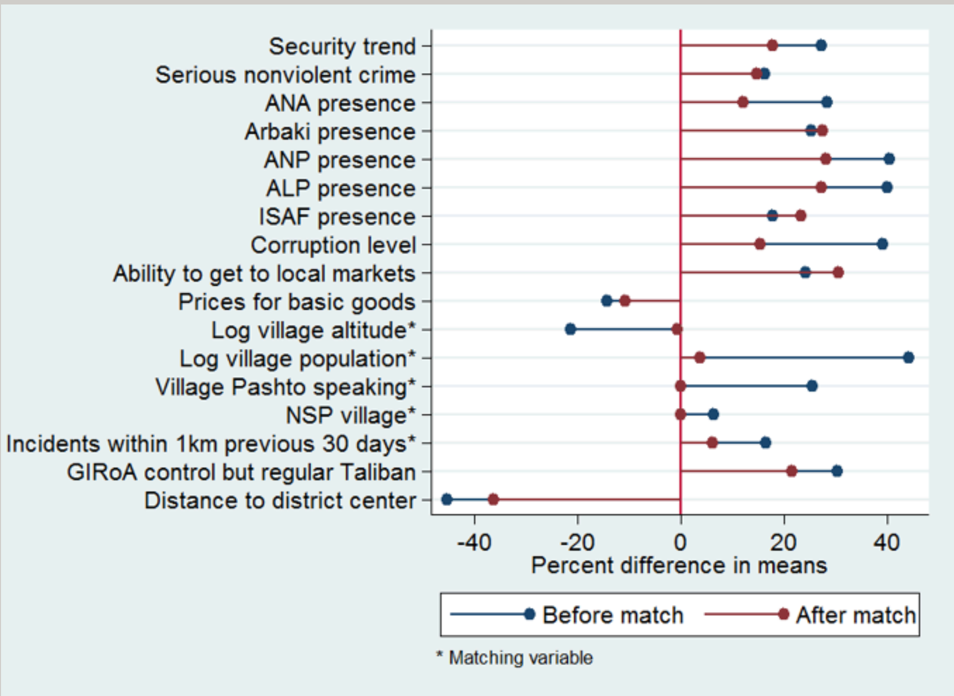
MISTI Treatment Timings

Wave	Comparison Villages	Treated Villages	Cumulative Treated
1	355	0	0
2	341	14	14
3	322	19	33
4	302	20	53
5	270	32	85

Before Estimation, Matching

Doubly-robust estimation

- Match on all variables that predict treatment and outcome
- Coursened Exact Matching



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	.031	.043	.003	-.039	-.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	Standard Error	t statistic	p value
Treatment	-.0389	.0947	-.411	.681

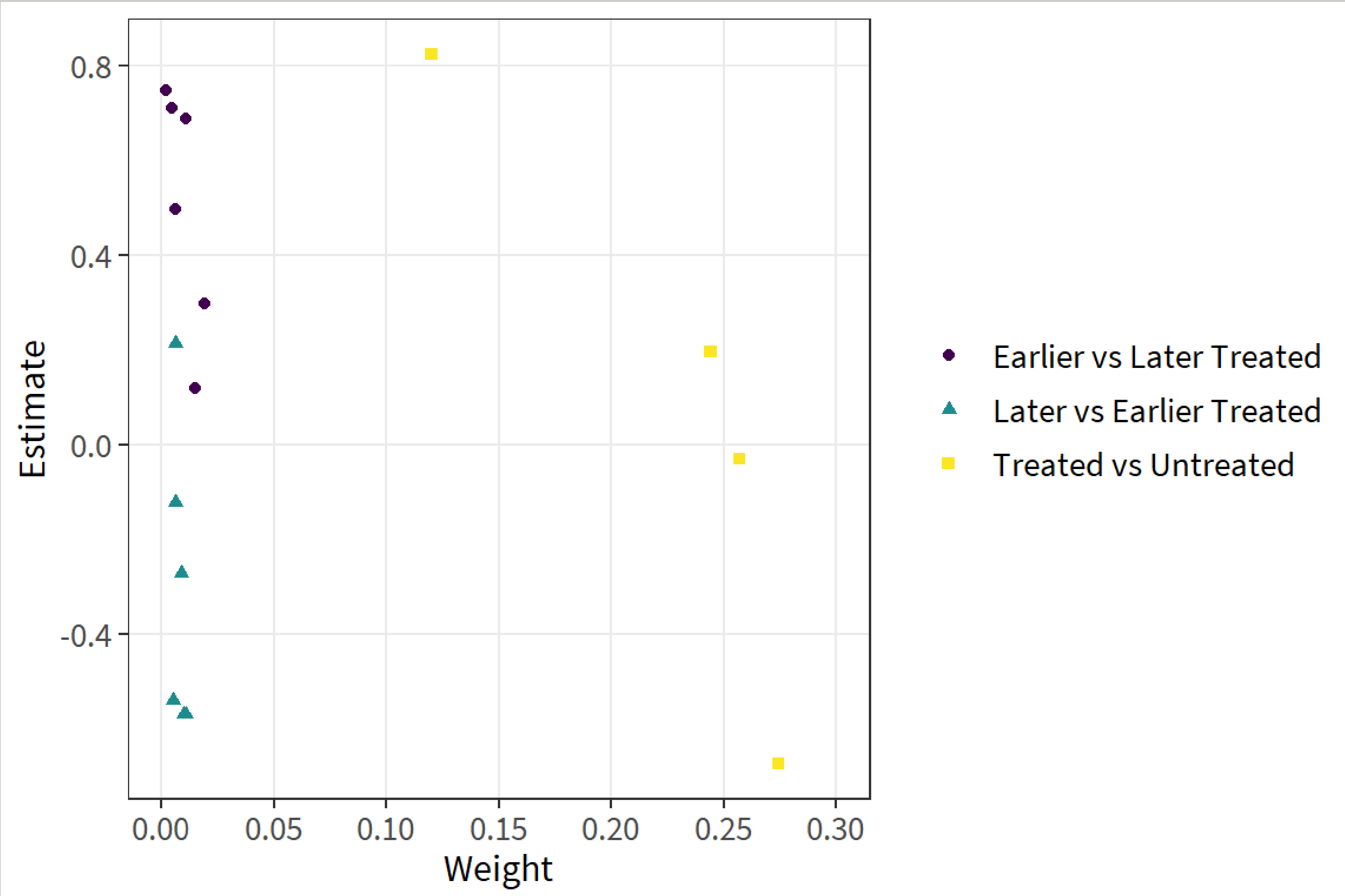
Diagnostic: the Bacon Decomposition

- 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 2x2 Cells

treated	untreated	estimate	weight	type
4	5	0.1182	0.01524	Earlier vs Later Treated
3	5	0.2976	0.01930	Earlier vs Later Treated
2	5	0.6868	0.01066	Earlier vs Later Treated
5	4	-0.5375	0.00508	Later vs Earlier Treated
3	4	0.4973	0.00603	Earlier vs Later Treated
2	4	0.7093	0.00444	Earlier vs Later Treated
5	99999	-0.6729	0.27424	Treated vs Untreated
4	99999	-0.0291	0.25710	Treated vs Untreated
3	99999	0.1964	0.24425	Treated vs Untreated
2	99999	0.8232	0.11998	Treated vs Untreated
5	3	-0.5686	0.00965	Later vs Earlier Treated
4	3	0.2135	0.00603	Later vs Earlier Treated
2	3	0.7473	0.00211	Earlier vs Later Treated
5	2	-0.5680	0.01066	Later vs Earlier Treated
4	2	-0.2707	0.00889	Later vs Earlier Treated
3	2	-0.1216	0.00633	Later vs Earlier Treated

Plot of 2x2 Cells



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
```

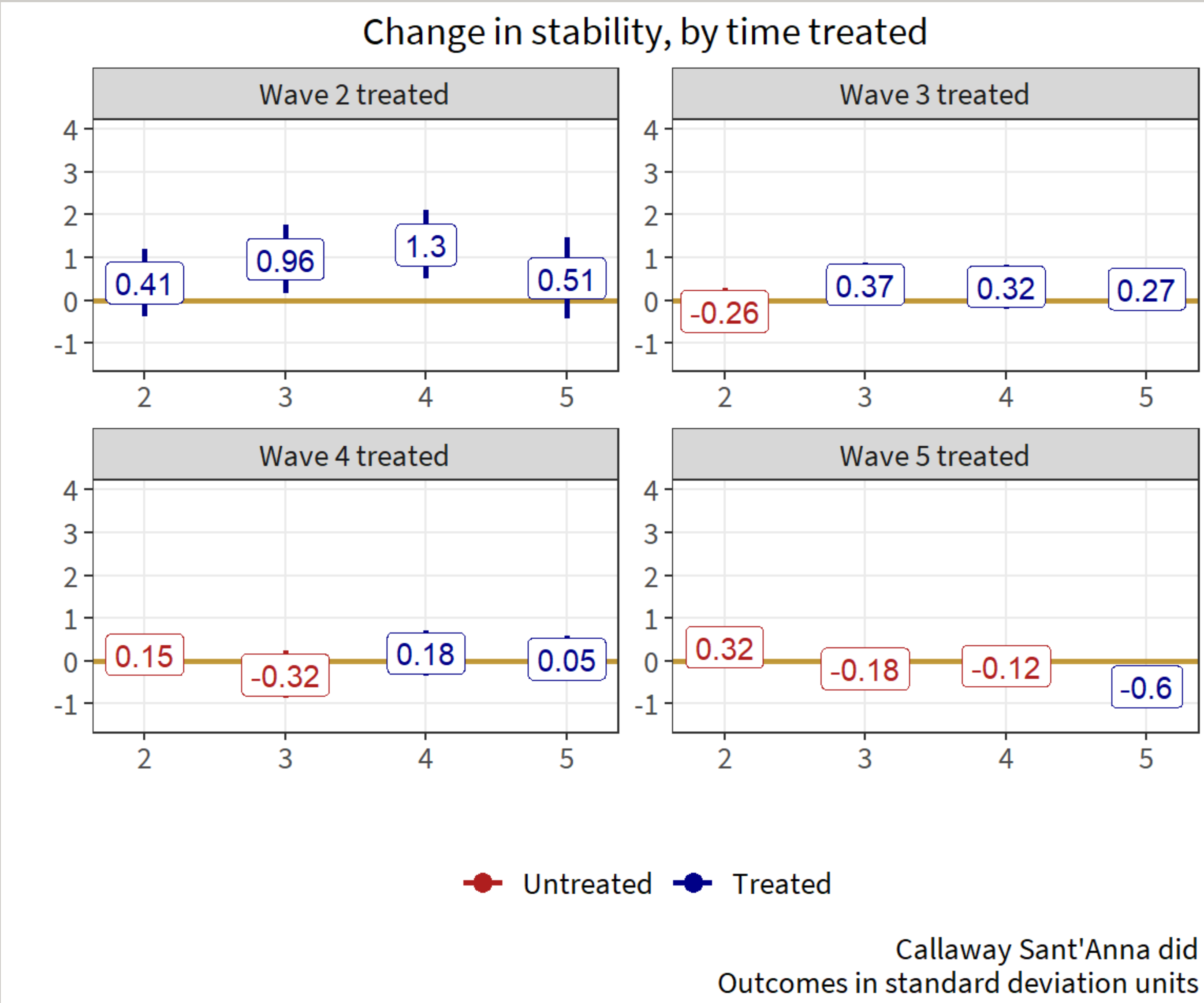
If the Bacon Decomposition reveals a problem, use the newer estimators

Callaway and Sant'Anna (2021)

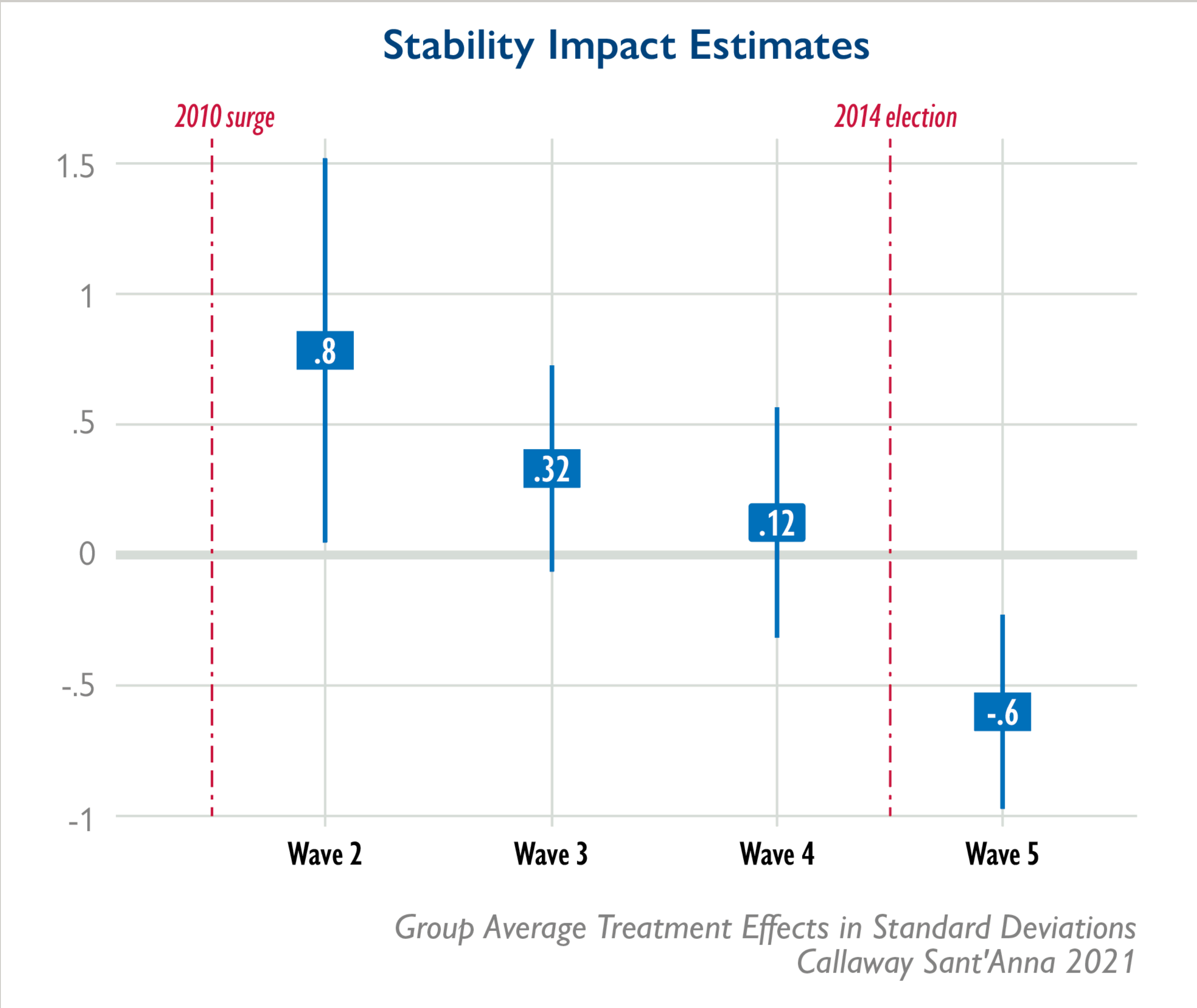
This estimation gives you multiple outcomes

- Estimates for each treated group at each treated period
- Dynamic treatment effects for each treated group
- Aggregate treatment effect for each treatment group
- Overall treatment effect across all groups and periods, after discarding biased 2x2 cells

Treatment Effects for Each Group-Wave



Aggregate Treatment Effects by Group



What Have We Learned About MISTI?

- Using the newer econometric estimators, we were able to show dynamic treatment effects across time
- These dynamic effects highlighted initial success of the 2010 surge
- Early success gradually declined until the legitimacy crisis of the 2014 election

What Have We Learned About Evaluation?

- 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!!

Looking Ahead

Stay tuned for sessions on:

- Logic modeling
- Learning agendas
- Mapping

Thank you!