

3. Difference-in-Differences

PhD Applied Methods

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Quick IV review: Compliance types are **fixed** attributes

Recall: an individual's compliance type is defined by the pair of **potential treatments**:

	$T_i(0) = 0$	$T_i(0) = 1$
$T_i(1) = 0$	Never-taker	Defier
$T_i(1) = 1$	Complier	Always-taker

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- This is a **fixed characteristic** of each person — does not depend on realized Z_i
- Avoid “ $T_i = 1$ when $Z_i = 1$ ” — this is a *realized outcome*, not a *type*
- Correct: $T_i(1) = 1$ and $T_i(0) = 0 \implies$ Complier

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Also: when computing type shares from a joint distribution table, **condition**:

$$P(T=1 \mid Z=1) = \frac{P(T=1, Z=1)}{P(Z=1)} \neq P(T=1, Z=1)$$

Defining a parameter \neq identifying it from data

A common pattern in causal inference:

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Lesson: Always ask: *who is in each comparison group?* If the type composition differs, your estimator may not identify your target parameter — even if it is well-defined.

Different instruments \Rightarrow different IV estimates

Angrist & Imbens (1995) show that with **multi-valued treatment**, IV identifies a weighted average of margin-specific LATEs — and the **weights depend on the instrument**.

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Concrete example: Two instruments for years of schooling

Instrument	Compliers	Margin
Compulsory schooling laws	Students pushed from dropping out to staying	$8 \rightarrow 9$, $9 \rightarrow 10$ years
College proximity	Students induced to attend college	$12 \rightarrow 13$, $13 \rightarrow 16$ years

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- Both are valid instruments for “the effect of education on earnings”
- But they identify effects for **different complier populations** at **different margins**
- Different IV estimates \neq one instrument is invalid

Different instruments \Rightarrow different IV estimates (cont.)

Why does this happen?

- With heterogeneous treatment effects, the return to an extra year of schooling differs across individuals and across margins (e.g., $8 \rightarrow 9$ vs. $15 \rightarrow 16$)

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Implication: IV estimates are *instrument-dependent*. When comparing IV results across studies, always ask: who are the compliers, and which treatment margin is being affected?

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Today: **Difference-in-Differences (DiD)**

- Applicable when there is both **temporal** and **cross-sectional** variation in treatment exposure
- Identifies causal effects under a **stronger assumption** (parallel trends) — but one that is often plausible in policy settings

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- One of the most widely used methods in applied economics

The fundamental problem

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Selection bias: treated and untreated groups differ systematically, even in the absence of treatment

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- **Difference-in-Differences (DiD)** is one of the most widely used methods in applied econometrics
- **Key insight:** Even if treated and control groups differ in levels, we can still identify causal effects if they share common trends
- Requires observing both groups **before and after** treatment
 - Use the change in the control group to construct the counterfactual for the treated group

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- **Difference-in-Differences (DiD)** is one of the most widely used methods in applied econometrics
- **Key insight:** Even if treated and control groups differ in levels, we can still identify causal effects if they share common trends
- Requires observing both groups **before and after** treatment
 - Use the change in the control group to construct the counterfactual for the treated group
- **Today's goal:** Understand the mechanics, assumptions, and extensions of DiD

Outline

1. Motivation
2. Theory: Common trends and graphical intuition
3. Multiple time periods, pre-trends, and regression
4. Threats to identification
5. Triple differences
6. Staggered treatment timing
7. Synthetic DiD

The naive before-after estimator

One approach: compare the treated group before and after treatment

Suppose we have:

- Period 1 (before treatment): $t = 1$
- Period 2 (after treatment): $t = 2$
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Question: What assumption is needed for this to identify the ATT?

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Interpretation: The treated group's outcome (absent treatment) would have been the same in both periods

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- **Life-cycle effects:** aging, experience accumulation, depreciation
- **Seasonality:** quarterly or monthly patterns
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Example: NJ minimum wage increase in 1992

- Employment in fast-food rises from 20.4 to 21.0
- If economy is booming \implies underestimates negative effect (or overestimates positive effect)
- If economy is in recession \implies overestimates negative effect

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Formally:

$$\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] = \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \quad (9)$$

Common trends: Intuition

The common trends assumption says:

- Treated and control groups can differ in **levels**
 - $\mathbb{E}[Y_{i,1}(0)|D_i = 1] \neq \mathbb{E}[Y_{i,1}(0)|D_i = 0]$ ✓

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 - Common time shocks that affect everyone
- This rules out:
 - Group-specific time trends
 - Differential exposure to time-varying shocks

Equivalence: Two ways to state parallel trends

The parallel trends assumption can be stated in two equivalent ways:

1. Changes are equal:

$$\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] = \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \quad (10)$$

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2. Selection bias is constant over time:

$$\underbrace{\mathbb{E}[Y_{i,1}(0)|D_i = 1] - \mathbb{E}[Y_{i,1}(0)|D_i = 0]}_{\text{Selection bias in } t=1} = \underbrace{\mathbb{E}[Y_{i,2}(0)|D_i = 1] - \mathbb{E}[Y_{i,2}(0)|D_i = 0]}_{\text{Selection bias in } t=2} \quad (11)$$

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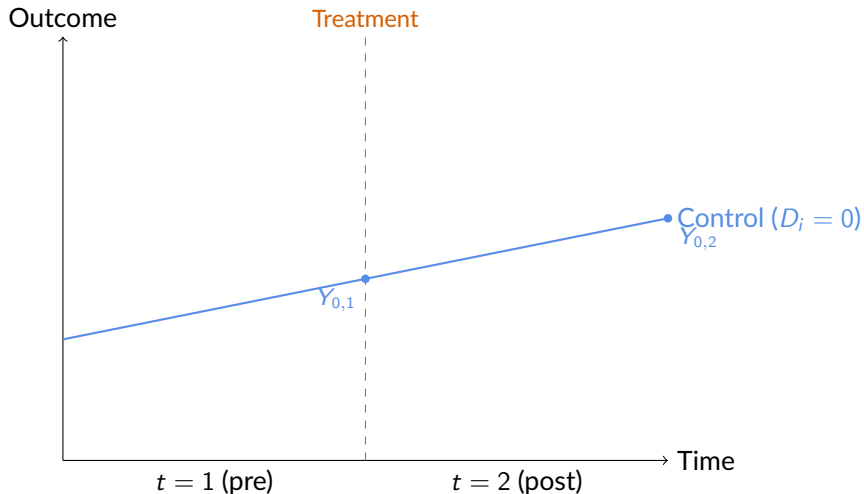
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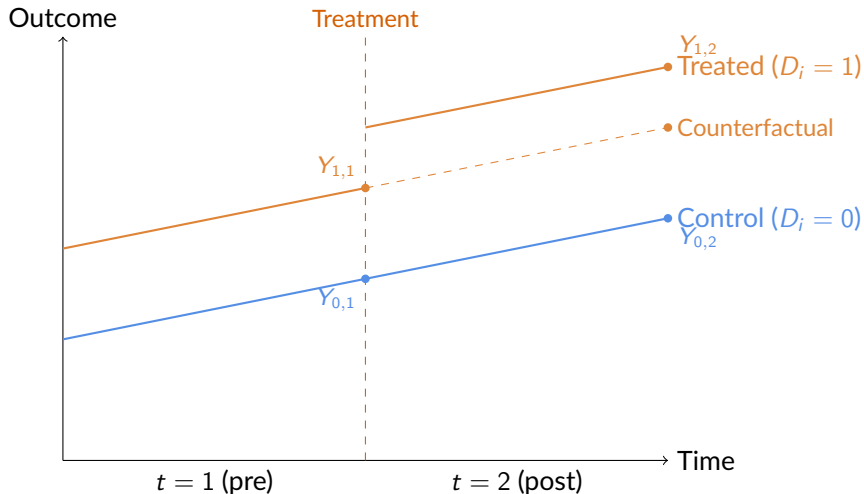
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Interpretation: The "gap" between treated and control (absent treatment) stays constant

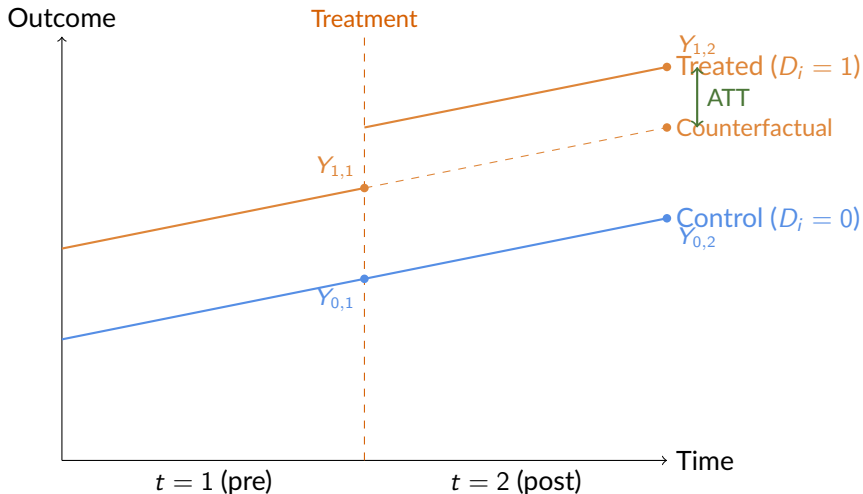
Graphical intuition: Difference-in-Differences



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Key insight: The change in the control group gives us the counterfactual trend for the

The 2×2 difference-in-differences estimator

We observe four group-time averages:

	Pre-treatment ($t = 1$)	Post-treatment ($t = 2$)
Treated ($D_i = 1$)	$Y_{1,1}$	$Y_{1,2}$
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The **difference-in-differences estimator** is:

$$\hat{\tau}^{DiD} = (\bar{Y}_{1,2} - \bar{Y}_{1,1}) - (\bar{Y}_{0,2} - \bar{Y}_{0,1}) \quad (12)$$

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- First difference: change in treated group over time
- Second difference: change in control group over time
- DiD: difference between these two changes

Alternative formulation

The DiD estimator can equivalently be written as:

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Interpretation:

- First difference: post-treatment difference between treated and control
- Second difference: pre-treatment difference between treated and control
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Interpretation:

- First difference: post-treatment difference between treated and control
- Second difference: pre-treatment difference between treated and control
- DiD: how much the gap changed

This formulation makes clear that DiD **differences out** time-invariant differences between groups

What does DiD identify?

Under the parallel trends assumption:

$$\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] = \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \quad (15)$$

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the DiD estimator identifies the ATT:

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Proof sketch:

$$\mathbb{E}[\hat{\tau}^{DiD}] = \mathbb{E}[Y_{i,2}(1)|D_i = 1] - \mathbb{E}[Y_{i,1}(0)|D_i = 1] \quad (17)$$

$$- (\mathbb{E}[Y_{i,2}(0)|D_i = 0] - \mathbb{E}[Y_{i,1}(0)|D_i = 0]) \quad (18)$$

Proof (continued)

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Proof (continued)

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Add and subtract $\mathbb{E}[Y_{i,2}(0)|D_i = 1]$:

$$= \underbrace{\mathbb{E}[Y_{i,2}(1) - Y_{i,2}(0)|D_i = 1]}_{\tau_2^{ATT}} \quad (21)$$

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Proof (continued)

$$\mathbb{E}[\hat{\tau}^{DiD}] = \mathbb{E}[Y_{i,2}(1)|D_i = 1] - \mathbb{E}[Y_{i,1}(0)|D_i = 1] \quad (19)$$

$$- (\mathbb{E}[Y_{i,2}(0)|D_i = 0] - \mathbb{E}[Y_{i,1}(0)|D_i = 0]) \quad (20)$$

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Under parallel trends, the second term equals zero, so:

$$\mathbb{E}[\hat{\tau}^{DiD}] = \tau_2^{ATT} \quad (23)$$

DiD as a regression

The 2×2 DiD estimator can be implemented via regression:

$$Y_{it} = \alpha + \gamma \cdot \mathbb{1}(D_i = 1) + \lambda \cdot \mathbb{1}(t = 2) + \beta \cdot \mathbb{1}(D_i = 1) \times \mathbb{1}(t = 2) + \varepsilon_{it} \quad (24)$$

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- $\mathbb{1}(D_i = 1)$: dummy for being in treated group
- $\mathbb{1}(t = 2)$: dummy for post-treatment period
- $\mathbb{1}(D_i = 1) \times \mathbb{1}(t = 2)$: interaction (treatment indicator)
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Key result: $\hat{\beta}_{OLS} = \hat{\tau}^{DiD}$

Understanding the regression coefficients

$$Y_{it} = \alpha + \gamma \cdot \mathbb{1}(D_i = 1) + \lambda \cdot \mathbb{1}(t = 2) + \beta \cdot \mathbb{1}(D_i = 1) \times \mathbb{1}(t = 2) + \varepsilon_{it} \quad (25)$$

What do the parameters represent?

	$t = 1$	$t = 2$
$D_i = 0$	α	$\alpha + \lambda$
$D_i = 1$	$\alpha + \gamma$	$\alpha + \gamma + \lambda + \beta$

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$D_i = 1$	$\alpha + \gamma$	$\alpha + \gamma + \lambda + \beta$

- α : baseline outcome (control, pre-period)
- γ : pre-treatment difference between groups
- λ : time trend (common to both groups)
- β : treatment effect (DiD estimator)

Verifying $\hat{\beta} = \hat{\tau}^{DiD}$

From the regression:

$$\beta = \mathbb{E}[Y_{it}|D_i = 1, t = 2] - \mathbb{E}[Y_{it}|D_i = 0, t = 2] \quad (26)$$

$$- (\mathbb{E}[Y_{it}|D_i = 1, t = 1] - \mathbb{E}[Y_{it}|D_i = 0, t = 1]) \quad (27)$$

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Rearranging:

$$\beta = (\mathbb{E}[Y_{it}|D_i = 1, t = 2] - \mathbb{E}[Y_{it}|D_i = 1, t = 1]) \quad (28)$$

$$- (\mathbb{E}[Y_{it}|D_i = 0, t = 2] - \mathbb{E}[Y_{it}|D_i = 0, t = 1]) \quad (29)$$

$$= \hat{\tau}^{DiD} \quad (30)$$

Two-way fixed effects (TWFE) formulation

With panel data, we can rewrite the DiD regression more compactly using fixed effects:

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot D_{it} + \varepsilon_{it} \quad (31)$$

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Equivalence: This is just a reparameterization of the dummy variable regression

- α_i absorbs all time-invariant unit characteristics
- δ_t absorbs all time-varying shocks common to all units

TWFE: Extending to $T > 2$ periods

The TWFE formulation naturally extends to multiple time periods:

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot D_{it} + \varepsilon_{it}, \quad t = 1, 2, \dots, T \quad (32)$$

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Parallel trends assumption: $Y_{it}(0) = \alpha_i + \delta_t + \varepsilon_{it}$ for all t

Example: Card & Krueger (1994)

Question: What is the effect of minimum wage on employment?

Setting:

- New Jersey raised minimum wage from \$4.25 to \$5.05 in April 1992
- Pennsylvania (neighboring state) did not change minimum wage
- Focus on fast-food restaurants (low-wage sector)

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Data:

- Survey of fast-food restaurants in NJ and PA
- Before (February 1992) and after (November 1992) treatment
- Outcome: full-time equivalent (FTE) employment

Card & Krueger: Results

	Before (Feb 1992)	After (Nov 1992)	Change
NJ (treated)	20.44	21.03	+0.59
PA (control)	23.33	21.17	-2.16
Difference	-2.89	-0.14	

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$$\hat{\tau}^{DiD} = 0.59 - (-2.16) = 2.75 \text{ FTE workers} \quad (33)$$

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Interpretation: Minimum wage increase led to a *relative* increase of 2.75 FTE workers in NJ restaurants (contrary to standard theory prediction)

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So far: basic 2×2 setup with $t \in \{1, 2\}$

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- Multiple pre-treatment periods: $t < t_0$
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- Multiple pre-treatment periods: $t < t_0$
- Multiple post-treatment periods: $t \geq t_0$
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Benefits of multiple time periods:

- ① Can test the parallel trends assumption using pre-treatment data
- ② Can study dynamic treatment effects (how effects evolve over time)
- ③ Can incorporate more flexible specifications

TWFE with multiple periods

With $T > 2$ periods, the TWFE specification becomes:

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot D_{it} + \varepsilon_{it} \quad (34)$$

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Interpretation of β :

- Average treatment effect across all treated units and time periods
- Assumes treatment effect is constant over time (homogeneous effects)
- We'll see later this can be problematic with staggered treatment timing

Testing the parallel trends assumption

The **Fundamental problem** is the assumption about **counterfactual** outcomes

- We can never directly observe $Y_{it}(0)$ for treated units after treatment
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~~The Fundamental problem~~ The Fundamental problem: assumption about **counterfactual** outcomes

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But: We can check whether trends were parallel **before** treatment!

Pre-trends test:

- If parallel trends holds, we should see no pre-treatment differences in trends
- If we find differential pre-trends, this casts doubt on the assumption
- Not a perfect test, but provides evidence on plausibility

Event study specification

To test for pre-trends and examine dynamic effects, use an **event study** design:

$$Y_{it} = \alpha_i + \delta_t + \sum_{\substack{k=-K \\ k \neq -1}}^L \beta_k \cdot \mathbb{1}(t - t_0^i = k) + \varepsilon_{it} \quad (35)$$

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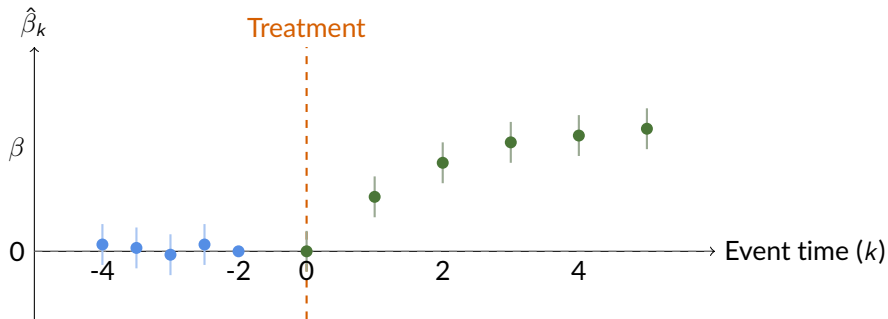
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Coefficients:

- β_k for $k < 0$: pre-treatment “effects” (should be zero if parallel trends holds)
- β_k for $k \geq 0$: post-treatment effects (dynamic treatment effects)

Event study: Graphical display

Typical event study plot:



Good pre-trends: Flat, close to zero before treatment (blue dots)

Treatment effects: Jump and evolution after treatment (green dots)

Pre-trends: What to look for

When examining pre-trends, check:

- 1 **Statistical significance:** Are pre-treatment $\hat{\beta}_k$ significantly different from zero?
 - Test individually: $H_0 : \beta_k = 0$ for each $k < 0$
 - Test jointly: $H_0 : \beta_{-K} = \dots = \beta_{-2} = 0$

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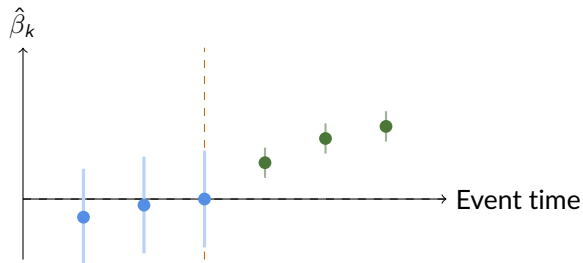
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 - Should be able to reject pre-trends as large as the treatment effect
- ④ **Number of pre-periods:** More pre-periods \implies more power to detect violations
 - With few pre-periods, tests have low power
 - Ideally want multiple pre-periods to credibly test parallel trends

Pre-testing concern 1: Power (Roth, 2022)

Problem: Standard pre-trends tests have low power

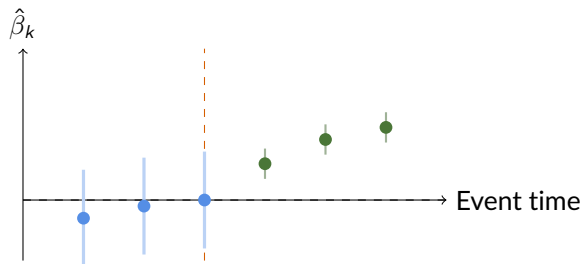
Consider this event study:



Pre-testing concern 1: Power (Roth, 2022)

Problem: Standard pre-trends tests have low power

Consider this event study:



Issue: Pre-trends not significant, but:

- Clear upward trajectory before treatment
- Confidence intervals VERY wide in pre-period

Ways of dealing with imprecise or differential pre-trends

- **Report pre-trends** - report the size of the pre-trend that can be rejected at conventional levels, and discuss how this compares to the estimated treatment effect (should ideally be able to reject that pre-trend is smaller than the treatment effect)

Ways of dealing with imprecise or differential pre-trends

- **Report pre-trends** - report the size of the pre-trend that can be rejected at conventional levels, and discuss how this compares to the estimated treatment effect (should ideally be able to reject that pre-trend is smaller than the treatment effect)
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- **Report pre-trends** - report the size of the pre-trend that can be rejected at conventional levels, and discuss how this compares to the estimated treatment effect (should ideally be able to reject that pre-trend is smaller than the treatment effect)
- **Bounding estimators** (Rambachan & Roth ReStud 2023) - use information from pre-trends to bound post-trend using an assumption on smooth changes in trends over time
- **Control for linear pre-trends** - you can also just include estimates of linear differential pre-trends in your DiD regression

- Intuitive proposed solution for robustness. Note the post and pre effects:

Rambachan and Roth (2023) suggestion

$$\mathbb{E}[\hat{\beta}_1] = \tau_{ATT} + \underbrace{\mathbb{E}[Y_{t,1}(0) - Y_{t,0}(0)|D_i = 1] - \mathbb{E}[Y_{t,1}(0) - Y_{t,0}(0)|D_i = 0]}_{\text{Post-period differential trend} =: \delta_1}$$

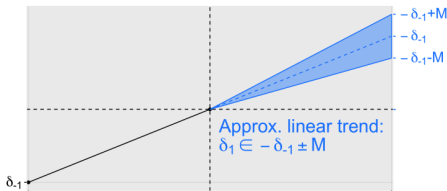
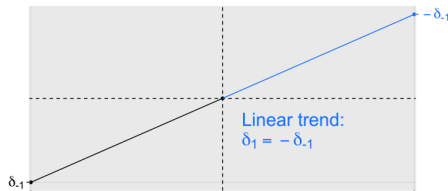
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- parallel trends assumes these δ are zero. But pre-trends may not be zero.
 - R&R say: we can use the info from our pre-trends to bound post-trend
 - Use a smoothness assumption, M , on the second derivative. E.g. simple case:



Standard errors in panel DiD

Important: With panel data, standard errors must account for correlation

Problem: Bertrand, Duflo & Mullainathan (2004)

- Outcomes for same unit are serially correlated over time
- ε_{it} and $\varepsilon_{it'}$ are correlated for $t \neq t'$
- Standard OLS standard errors are severely downward biased
- Leads to massive over-rejection of null hypotheses

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Solution: Cluster standard errors at the unit level

- Allows arbitrary correlation within units over time
- Conservative: only assumes independence across units
- In Stata: `reg Y X, cluster(unit_id)`
- In R: `lm_robust(Y ~ X, clusters = unit_id)`
- With fixed effects in R: `feols(Y ~ D | unit + time, cluster = "unit", data = df)`
from the `fixest` package (fast and flexible clustering specification)

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Main threats to DiD identification

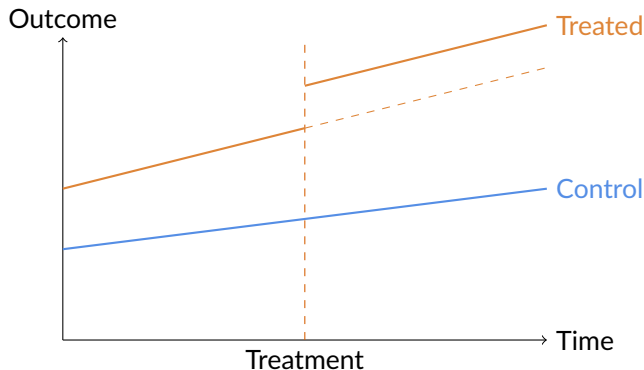
The parallel trends assumption can be violated in several ways:

- ① **Differential trends:** Treated and control groups on different trajectories
- ② **Differential shocks:** Time-varying shocks that affect groups differently
- ③ **Selection into treatment** (Ashenfelter's dip)
- ④ **Anticipation effects:** Behavioral responses before treatment
- ⑤ **Spillover effects:** Treatment affects control group
- ⑥ **Composition changes:** Different units in cross-sectional DiD
- ⑦ **Functional form:** Parallel trends in logs vs. levels

Let's discuss each in turn...

Threat 1: Differential trends

Problem: Treated and control groups on systematically different trajectories



Example: Regions with strong economic growth more likely to get infrastructure investment

Dealing with differential trends

Solutions:

1. Group-specific linear trends:

$$Y_{it} = \alpha_i + \delta_t + \gamma_i \cdot t + \beta \cdot D_{it} + \varepsilon_{it} \quad (36)$$

- γ_i : unit-specific linear time trend
- Allows for different slopes across units
- But: mechanically reduces post-treatment differences

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- Allows for different slopes across units
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2. Rambachan & Roth (2023) sensitivity analysis:

- Bound treatment effects under violations of parallel trends
- Assume trend violations can't be "too large"
- Provides robust confidence intervals

Threat 2: Differential shocks

Problem: Time-varying shock affects treated and control groups differently

Example: Minimum wage study

- NJ raises minimum wage; PA does not
- But NJ also experiences a state-specific recession
- Employment falls in NJ for two reasons: minimum wage + recession
- DiD incorrectly attributes recession effect to minimum wage

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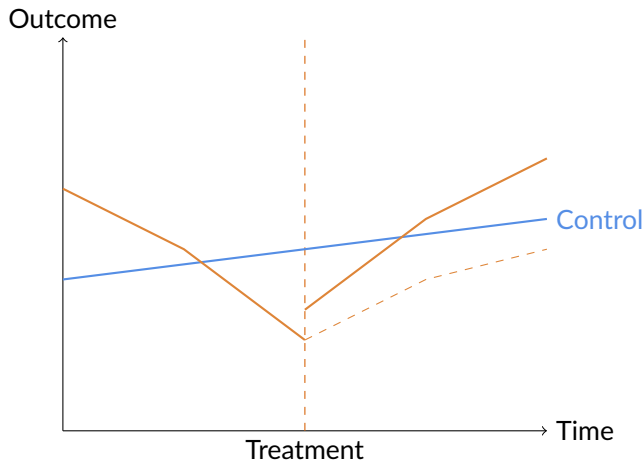
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Solutions:

- Find better control groups (similar in all dimensions)
- Use multiple control groups to test robustness
- Look for placebo outcomes (unaffected by treatment)
- Triple differences (if another dimension available)

Threat 3: Ashenfelter's dip

Problem: Units select into treatment precisely because they're on a downward trajectory



Ashenfelter's dip: Evidence and solutions

• Study of Ashenfelter (1978): Names after Ashenfelter program

- Found workers' earnings decline sharply before enrollment
- Then recover after training
- But hard to tell if recovery is due to training or mean reversion

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- Found workers' earnings decline sharply before enrollment
- Then recover after training
- But hard to tell if recovery is due to training or mean reversion

Critical point: Ashenfelter's dip can be on **unobservables!**

- Even if pre-trends in observed outcomes look parallel, unobserved factors may differ
- Example: Workers enroll when motivation/health declines (unobservable)
- **Fundamentally untestable** — can't see unobservables in pre-period
- Clean pre-trends are reassuring but not definitive proof
- Threatens any setting where units select into treatment

Solutions to Ashenfelter's dip

Solutions:

- ① Look for the dip in pre-treatment data (event study)
 - If present in observables, likely worse in unobservables
- ② If present, focus on longer pre-treatment differences
- ③ Match treated units to controls experiencing similar pre-treatment trajectory
- ④ Use alternative control groups (e.g., future trainees)
- ⑤ **Best solution:** Find settings where treatment timing is plausibly exogenous
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Takeaway: Be skeptical of DiD when treatment is chosen precisely when units need it most

Threat 4: Anticipation effects

Problem: Units change behavior in anticipation of treatment

Example: Tax policy announced in advance

- Firms know corporate tax will increase next year
- Shift profits to current year to avoid higher future tax
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- "Leads" ($k < 0$) should be zero under no anticipation

Solutions:

- Use earlier pre-period as baseline (before announcement)
- Model anticipation explicitly if timing is known

Threat 5: Spillover effects

Problem: Treatment of one group affects outcomes in control group

Example: Job training program

- Treated workers become more productive
- Firms substitute away from untrained workers
- Control group employment falls
- DiD overestimates treatment effect (includes spillover)

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Solutions:

- Choose geographically distant control groups
- Look for evidence of spillovers in untreated outcomes
- Model equilibrium effects explicitly (general equilibrium)
- Acknowledge limitation in interpretation

Threat 6: Composition changes

Problem: In repeated cross-sections, different individuals in each period

Example: Regional minimum wage study

- High-wage workers migrate to treated region after treatment
- Average wage appears to increase
- But this is composition, not causal effect on incumbent workers

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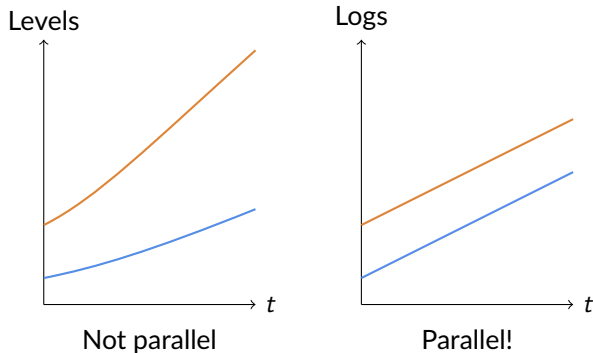
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Solutions:

- ① Use panel data (follow same individuals)
- ② Test whether observable characteristics change
- ③ Control for composition using reweighting
- ④ Focus on intensive margin (hours) not extensive (employment)

Threat 7: Functional form

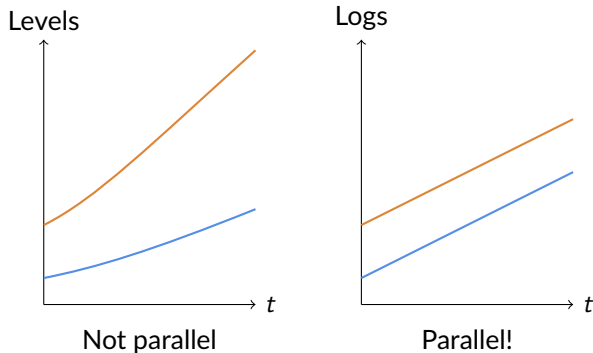
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The parallel trends assumption $\mathbb{E}[Y_{it}(0) - Y_{it'}(0)|D_i = 1] = \mathbb{E}[Y_{it}(0) - Y_{it'}(0)|D_i = 0]$ is scale-dependent:

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The question: Which functional form assumption is the right one for your setting?

- **Levels:** Additive treatment effects ($Y_{it}(1) = Y_{it}(0) + \tau$)
- **Logs:** Proportional treatment effects ($Y_{it}(1) = Y_{it}(0) \times (1 + \tau)$)

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$$Y_{it}(0) = h_t(U_i) \quad (37)$$

where U_i is a time-invariant unobserved heterogeneity term, and $h_t(\cdot)$ is a strictly increasing function that can vary over time

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Intuition: Use the change in the distribution of control group outcomes to construct counterfactual distribution for treated group

Why CIC is not commonly used in practice

① Sample requirements

- Quantile estimation is noisier than mean estimation
- Need larger samples for stable distributional estimates

② Still quite strong assumptions in practice

- The rank invariance assumption (individuals maintain their position in the distribution over time) is quite restrictive
- May be violated if there's genuine mobility in the outcome distribution
- Not obviously weaker than parallel trends in all applications

Choosing the right functional form

How to decide?

- ① **Economic theory:** Does the treatment have additive or multiplicative effects?
 - Tax policy: proportional (use logs)
 - Cash transfer: additive (use levels)

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- ④ **Be explicit:** State which functional form you assume and why
 - Don't pretend it's a minor technical detail
 - Acknowledge this is a maintained assumption

Outline

1. Motivation
2. Theory: Common trends and graphical intuition
3. Multiple time periods, pre-trends, and regression
4. Threats to identification
- 5. Triple differences**
6. Staggered treatment timing
7. Synthetic DiD

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- Control states: No program
- Concern: Treated states may have different macro trends (differential shocks)

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- Control states: No program
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Solution: Use men as an additional control group

- Men are not affected by the program (neither in treated nor control states)
- DiD on men captures differential macro shocks between states
- DiD on women captures differential shocks + treatment effect
- Triple difference = $\text{DiD}_{\text{women}} - \text{DiD}_{\text{men}}$ isolates treatment effect

Triple differences: Formula

Let: $D_s = 1$ for treated state, $= 0$ for control state

- $F_i = 1$ for female, $= 0$ for male
- $t = 1$ (pre), $t = 2$ (post)

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Triple difference:

$$DDD = DiD_F - DiD_M \quad (40)$$

Triple differences: Regression

Can implement via regression:

$$Y_{ist} = \alpha + \beta_1 D_s + \beta_2 F_i + \beta_3 Post_t \quad (41)$$

$$+ \beta_4 (D_s \times F_i) + \beta_5 (D_s \times Post_t) + \beta_6 (F_i \times Post_t) \quad (42)$$

$$+ \beta_7 (D_s \times F_i \times Post_t) + \varepsilon_{ist} \quad (43)$$

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Key coefficient: β_7 is the DDD estimator

Assumption required:

- Men and women in the same state are subject to the same differential shocks
- Common trends for men and women would have been parallel (in differences)

Triple differences: When to use

Advantages: Differs out state-specific shocks that affect both genders

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- Provides robustness check even if not primary specification

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Disadvantages:

- Requires finding a truly "unaffected" group
- Stronger assumptions (parallel trends for the difference-in-trends)
- Less precise (more differences = more noise)
- Spillovers to "unaffected" group would bias results

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So far: single treatment period (t_0), all treated units adopt simultaneously

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- Individuals age into eligibility at different times

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- Firms receive treatment based on phased rollout
- Individuals age into eligibility at different times

Benefits of staggered rollout:

- ① More robust to macro shocks
 - Units treated at different times face different macro conditions
 - Differential shocks less likely to confound all comparisons
- ② Can use earlier-treated as controls for later-treated (and vice versa)

Example: Yagan vs. Goodman-Bacon

Yagan (2015): State-level capital gains tax cuts and entrepreneurship

- All cuts happen in one year (1992)
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Better design: Staggered rollout across years

- Some states cut in 1990, others in 1992, others in 1995...
- Macro shocks in different years unlikely to align with treatment
- More credible parallel trends assumption

The problem with TWFE and staggered timing

Historically: Researchers used TWFE for staggered DiD

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot D_{it} + \varepsilon_{it} \quad (44)$$

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Recent discovery: This doesn't work with:

- ① Staggered treatment timing, AND
- ② Heterogeneous treatment effects

Goodman-Bacon decomposition (2 treatment times)

Goodman-Bacon (2021): Special case with 2 treatment times

With two treatment cohorts (early and late) plus never-treated, TWFE is a weighted average of three 2×2 comparisons:

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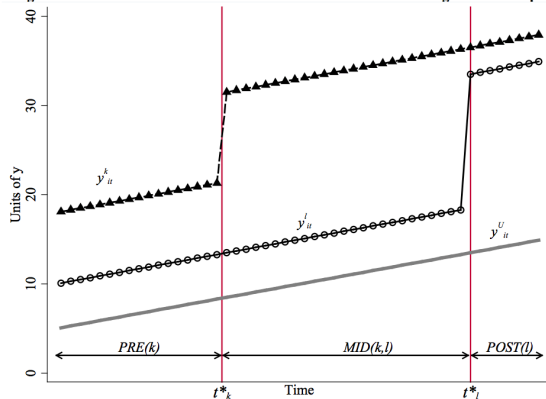
③ **Later-treated vs. earlier-treated**

- Weight: variance share
- Sign: **can be negative** (forbidden comparison!)
- Earlier-treated serves as "control" for later-treated
- But earlier-treated is already experiencing treatment effects

Goodman-Bacon 2×2 comparisons

- Consider two staggered treatments and a never-treated group
- What does the TWFE estimator estimate?
- TWFE decomposes into all possible 2×2 comparisons

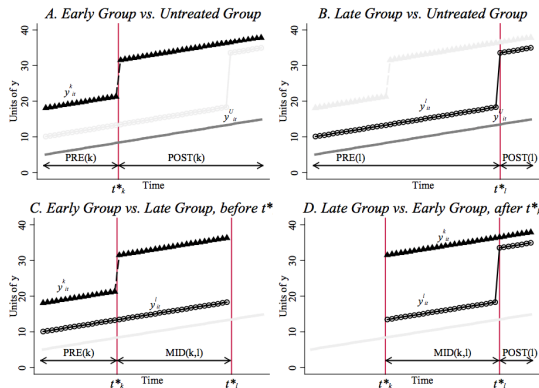
Figure 1. Difference-in-Differences with Variation in Treatment Timing: Three Groups



The forbidden comparison problem

- Weighting becomes problematic if effects vary over time

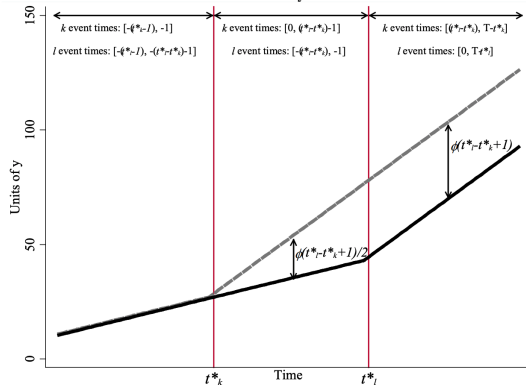
Figure 2. The Four Simple (2x2) Difference-in-Differences Estimates from the Three Group Case



The forbidden comparison problem

- Weighting becomes problematic if effects vary over time
- With time-varying effects, already-treated units are bad controls
- This creates **negative weights** on some treatment effects
- Goodman-Bacon decomposition reveals how much weight is problematic

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



Heterogeneous treatment effects: 3-group example

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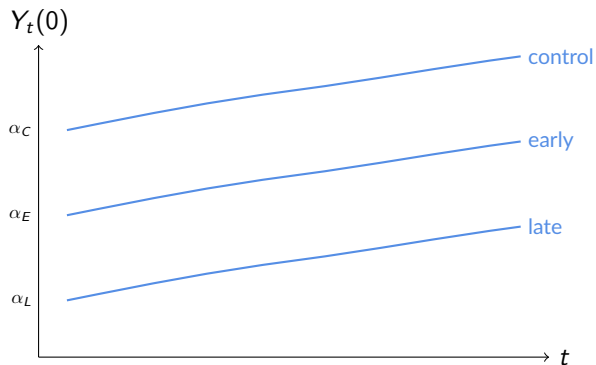
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Potential source of problems: Treatment effects are **dynamic** (grow with exposure):

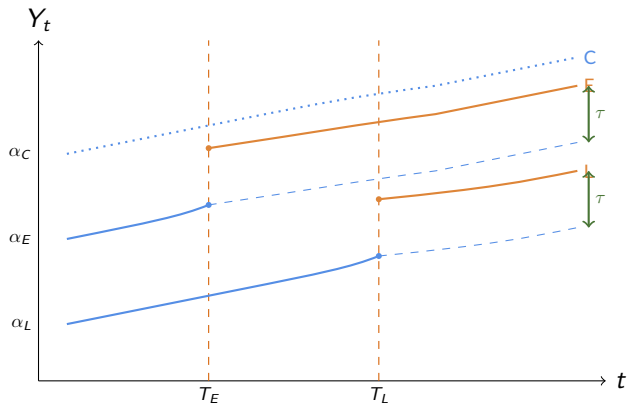
- Effect is τ_l in first period after treatment
- Effect grows to τ_h in second period after treatment (where $\tau_h > \tau_l$)
- **Problem:** Group E has been treated longer at $t = 3$ than Group L

Parallel trends: All groups share common $g(t)$

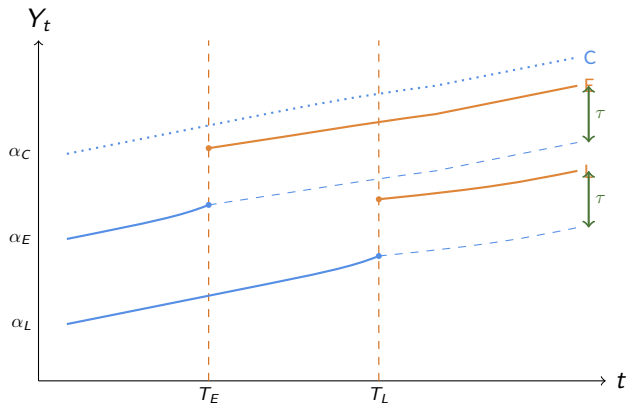


All three curves have same shape (parallel) but different levels ($\alpha_C > \alpha_E > \alpha_L$)

With constant treatment effects: τ (no dynamics)



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Constant treatment effects: τ remains the same over time (no problem for TWFE)

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The forbidden comparison now gives:

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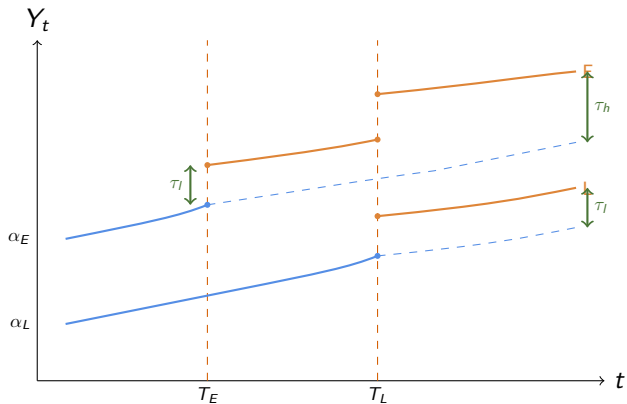
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Key insight: With constant effects, all valid comparisons give the same answer τ

- No contamination from using already-treated units as controls
- TWFE works fine when treatment effects don't change over time

With dynamic treatment effects: $\tau_l < \tau_h$



Dynamic treatment effects: Effects grow from τ_l to τ_h with exposure (problem for TWFE!)

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- Group L just got treated \Rightarrow effect is τ_l

TWFE's implicit estimate from this comparison:

$$\begin{aligned}
 \hat{\tau}_{L \text{ vs } E}^{TWFE} &= [Y_{L, T_L} - Y_{L, T_E}] - [Y_{E, T_L} - Y_{E, T_E}] \\
 &= [\alpha_L + g(T_L) + \tau_l - \alpha_L - g(T_E)] \\
 &\quad - [\alpha_E + g(T_L) + \tau_h - \alpha_E - g(T_E) - \tau_l] \\
 &= \tau_l - (\tau_h - \tau_l) \\
 &= 2\tau_l - \tau_h
 \end{aligned}$$

What TWFE estimates with dynamic effects

$$\hat{\tau}_{L \text{ vs } E}^{TWFE} = 2\tau_l - \tau_h$$

Problem: If $\tau_l < \tau_h$, this can give a **negative** estimate!

- Even though treatment has a positive effect at all horizons
- TWFE uses already-treated Group E (with large effect) as "control"
- Contaminates the estimate with **heterogeneity over time**: $2\tau_l - \tau_h$
- Really we care about the ATT or ATE $\approx (\tau_l + \tau_h)/2$. At the very least, τ_h should not be counting negatively towards our estimate of treatment effects!

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Implication:

- $\hat{\beta}^{TWFE}$ can be negative even if all $ATT_{g,t} > 0$
- Or vice versa: $\hat{\beta}^{TWFE} > 0$ even if all $ATT_{g,t} < 0$
- Cannot interpret $\hat{\beta}^{TWFE}$ as a meaningful average
- Their diagnostic tool shows how much negative weight in your data

Solutions to staggered timing problem

Don't use standard TWFE with staggered timing + heterogeneous effects!

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③ Sun & Abraham (2021):

- Event-study approach with interaction-weighted estimator
- Clean estimates of dynamic effects by cohort

Callaway & Sant'Anna (2021) estimator

Basic approach: Explicitly **exclude** any forbidden comparisons.

- 1 Define cohorts by treatment timing: $g \in \{2, 3, \dots, T, \infty\}$
 - $g = t$ if unit first treated at time t
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Key advantage: Transparent about what's being compared and weighted.

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Important: The staggered timing problem also applies to **fuzzy DiD**

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- Treatment occurs in the treatment group, but also (to lesser extent) in control group
- Example: Policy rollout affects neighboring regions
- Example: Media coverage spills over to control areas

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Why this matters:

- If control group has small treatment effect $\tau_C > 0$
- And treatment group has larger effect $\tau_T > \tau_C$
- Standard DiD estimates $\tau_T - \tau_C$, not τ_T
- This is the same issue as forbidden comparisons!
- Comparing "more treated" vs. "less treated" rather than "treated" vs. "untreated"

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Takeaway: Be careful about control group contamination and partial treatment

Practical recommendations

If you have staggered treatment timing:

① Check for heterogeneity:

- Run event study: do effects vary across cohorts or over time?
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④ Be transparent:

- Document which comparisons are being made
- Show event studies by cohort if heterogeneity is present
- Discuss sensitivity to choice of comparison group

Outline

1. Motivation
2. Theory: Common trends and graphical intuition
3. Multiple time periods, pre-trends, and regression
4. Threats to identification
5. Triple differences
6. Staggered treatment timing
7. Synthetic DiD

Synthetic control methods

Motivation: What if parallel trends doesn't hold for all control units?

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Key idea: Construct a **weighted combination** of control units that best matches the treated unit pre-treatment:

$$\tau = \underbrace{Y_{post}(1)}_{\text{Fully observed}} - \underbrace{\hat{Y}_{post}(0)}_{\text{Constructed}} \quad (48)$$

Synthetic Control example (Abadie et al., 2010))

- Consider following problem: California bans smoking in 1989. What does that do to smoking?
 - Define estimand:
$$\tau_{ban, CA} = Y_{california, post}(1) - Y_{california, post}(0)$$
 - This is the effect of the California smoking ban
 - How can we get at it?
- We need a “synthetic California” as our control
- In an ideal world, the average of the other states would work – however, not clear empirically that they are a good counterfactual

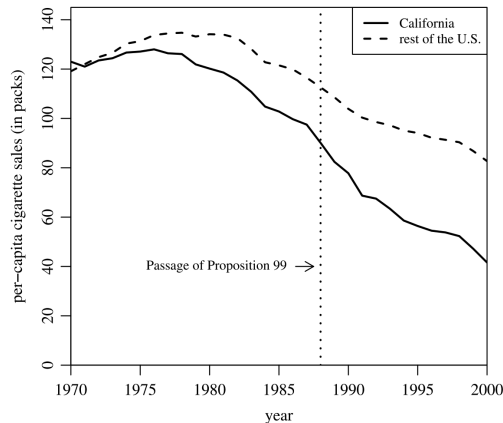


Figure 1. Trends in per-capita cigarette sales: California vs. the rest of the United States.

Synthetic control: basic method

Method (Abadie et al., 2010): $\sum_j \omega_j = 1$

- Estimate counterfactual untreated California using a weighted sum of other states that “look like” California (the synthetic California)

$$\hat{Y}_{\text{post,treated}}(0) = \sum_j \omega_j Y_{\text{post,control}}$$

- Select weights to make minimize the distance in terms of pre-treatment covariates:

$$\{\hat{\omega}\}_i = \arg \min_{\mathbf{W}} \|\mathbf{X}_{\text{treat}} - \mathbf{X}_{\text{control}} \mathbf{W}\|$$

- This approach can be incredibly successful

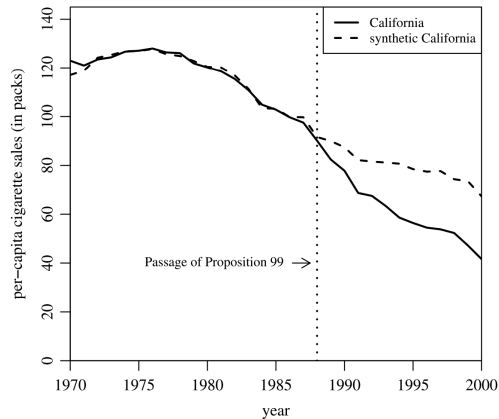


Figure 2. Trends in per-capita cigarette sales: California vs. synthetic California.

The synthetic control method (Abadie et al. (2010))

- This approach can be incredibly successful
- By careful construction of a synthetic control, can calculate counterfactual impacts due to policy
- Still subject to same caveats from DiD – not invariant to some transformations (e.g. log and linear)

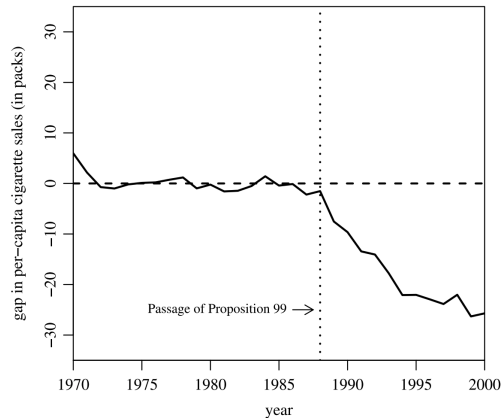


Figure 3. Per-capita cigarette sales gap between California and synthetic California.

Extension to synthetic DiD

Arkhangelsky et al. (2021): Combine unit weights and time weights

- **Unit weights (ω_i):** reweight controls so that their pre-outcomes match the treated units' pre-outcomes (same as synthetic control)
- **Time weights (λ_t):** reweight time so that for the controls, the pre-period looks like the post period
 - This soaks up aggregate trends
 - E.g., if there was a macroeconomic recession in the post-period, want to weight pre-periods more if there was a recession in those periods

Then do a **DiD** on this reweighted setup.

► More details on synthetic methods

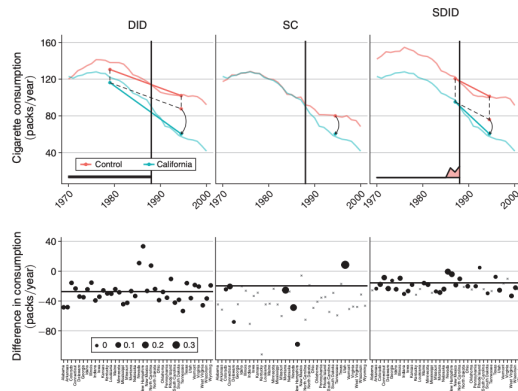


FIGURE 1. A COMPARISON BETWEEN DID, SC, AND SDID ESTIMATES FOR THE EFFECT OF CALIFORNIA PROPOSITION 99 ON PER-CAPITA ANNUAL CIGARETTE CONSUMPTION (IN PACKS/YEAR)

Summary: The DiD toolkit

Basic DiD (2x2 design) assumption: $\mathbb{E}[Y_{it}(0) - Y_{it'}(0)|D_i = 1] = \mathbb{E}[Y_{it}(0) - Y_{it'}(0)|D_i = 0]$

- Identifies ATT under parallel trends
- Can implement via regression: $Y_{it} = \alpha_i + \delta_t + \beta \cdot D_{it} + \varepsilon_{it}$

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Key threats:

- Differential trends, differential shocks, Ashenfelter's dip
- Anticipation, spillovers, composition, functional form

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Extensions:

- Triple differences for additional robustness
- Event studies for dynamic effects (with caution on pre-trends)

Summary: Recent developments

• Standard TWFE timing: negative weights with heterogeneous effects

- “Forbidden comparisons”: later-treated vs. already-treated
- **Solutions:** Callaway & Sant’Anna (2021), de Chaisemartin & D’Haultfoeuille (2020), Sun & Abraham (2021)

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Synthetic control methods:

- When parallel trends may not hold for all controls
- Construct weighted combination matching pre-treatment characteristics
- Transparent, data-driven approach to control group construction
- Best for few treated units with rich pre-treatment data

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Key takeaway: Choice of method depends on your setting, data structure, and assumptions you’re willing to make

Practical advice

① Always visualize your data:

- Plot trends for treatment and control groups
- Show event studies (but interpret pre-trends carefully)
- Make the parallel trends assumption transparent

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④ Document your choices:

- Which comparison groups are being used
- How you handle standard errors (clustering level)
- Sensitivity to key decisions

Thank you!

Questions?

Generalized panel setup

Consider a panel with T time periods and $N + 1$ units. Intervention D_{it} at time T_0 for one unit (unit $i = 0$).

Let $\mathbf{Y}_{a,b}$ denote outcomes for $a \in \{\text{treated, control}\}$ and $b \in \{\text{pre, post}\}$:

$$\mathbf{Y} = \begin{pmatrix} \mathbf{Y}_{t,\text{post}} & \mathbf{Y}_{c,\text{post}} \\ \mathbf{Y}_{t,\text{pre}} & \mathbf{Y}_{c,\text{pre}} \end{pmatrix} = \begin{pmatrix} \mathbf{Y}_{t,\text{post}}(1) & \mathbf{Y}_{c,\text{post}}(0) \\ \mathbf{Y}_{t,\text{pre}}(0) & \mathbf{Y}_{c,\text{pre}}(0) \end{pmatrix}$$

Key insight: We need to estimate $\mathbf{Y}_{t,\text{post}}(0)$, the counterfactual for the treated unit(s) in the post period.

Synthetic DiD: The estimator

Standard DiD:

$$(\hat{\alpha}, \hat{\gamma}, \hat{\tau}) = \arg \min \sum_{i,t} (Y_{it} - \alpha_i - \gamma_t - D_{it}\tau)^2$$

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Synthetic Control:

$$(\hat{\gamma}, \hat{\tau}) = \arg \min \sum_{i,t} (Y_{it} - \gamma_t - D_{it}\tau)^2 \hat{\omega}_i$$

where $\hat{\omega}_i$ chosen to match pre-treatment characteristics

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$$(\hat{\alpha}, \hat{\gamma}, \hat{\tau}) = \arg \min \sum_{i,t} (Y_{it} - \alpha_i - \gamma_t - D_{it}\tau)^2 \hat{\omega}_i \hat{\lambda}_t$$

where both $\hat{\omega}_i$ (unit weights) and $\hat{\lambda}_t$ (time weights) are data-driven

Generalized estimator form

Consider estimators of the form:

$$\hat{Y}_{t,\text{post}}(0) = \mu + \sum_{j \in \text{controls}} \omega_j Y_{j,T}$$

Components:

- μ : Constant allowing for level differences (common in DiD)
- ω_j : Weights that vary across control units
 - Simple average would be standard DiD
 - Different weights allow more flexibility

Question: How should we choose the weights ω_j ?

Synthetic control weight restrictions

Abadie, Diamond, Hainmueller (2010) impose three restrictions:

- ① $\mu = 0$ (no intercept)
- ② $\sum_j \omega_j = 1$ (weights sum to one)
- ③ $\omega_j \geq 0 \forall j$ (non-negative weights)

Interpretation:

- These create a counterfactual whose outcomes are **within the convex hull** of control units
- Treated unit is a weighted average of a subset of control states
- More transparent than allowing negative weights or extrapolation

Formal weight estimation

Weights ω_j are chosen by minimizing distance between covariates in pre-period:

$$\{\hat{\omega}_j\}_j = \arg \min_{\mathbf{W}} \|\mathbf{X}_{\text{treat}} - \mathbf{X}_{\text{control}} \mathbf{W}\|$$

subject to $\sum_j \omega_j = 1$ and $\omega_j \geq 0$.

Crucial feature: \mathbf{X} can include:

- Lagged outcomes: $Y_{i,t-1}, Y_{i,t-2}, \dots$
- Time-invariant covariates: demographics, geography, etc.
- Time-varying covariates

Re-envision the panel:

- **Observed outcomes:** $\mathbf{Y}_{t,\text{post}}(1), \mathbf{Y}_{c,\text{post}}(0)$
- **Covariates/predictors:** $\mathbf{Y}_{t,\text{pre}}(0), \mathbf{Y}_{c,\text{pre}}(0), \mathbf{X}_t, \mathbf{X}_c$

Inference with synthetic control

Challenge: With only one treated unit, standard large-sample asymptotics don't apply.

Standard approach: Placebo/permutation tests

- Apply synthetic control method to **each potential control unit**
- Compute “placebo effects” for untreated units
- Compare actual treatment effect to distribution of placebo effects
- Similar to randomization inference

Interpretation:

- If treatment effect is large relative to placebos \Rightarrow evidence of real effect
- If treatment effect is in middle of distribution \Rightarrow could be noise

Staggered adoption with synthetic DiD

Issue: Staggered adoption isn't as natural for synthetic control

- How can we adapt it?

Solution (following Callaway & Sant'Anna approach):

- Split up adoption timings by cohort
- Estimate synthetic DiD separately for each (g, t) pair
 - g = adoption cohort
 - t = time period
- Aggregate cohort-time effects

Advantage: Allows for heterogeneous treatment effects across cohorts and time while maintaining synthetic control benefits

Practical considerations and skepticism

Why limited adoption despite being “cool”?

Challenges:

- Strong structural assumptions
 - Not clear we have good tests yet
 - Pre-trends in DiD felt more testable/transparent
- Researcher degrees of freedom
 - Choice of covariates to match on
 - Which control units to include
 - How to weight different matching variables
 - True in DiD too, but perhaps less transparent?

Alternative interpretation:

- Maybe DiD is equally problematic, but we're not aware of it
- If we accept DiD is sensitive to functional form, then ML methods that construct counterfactuals are natural

Practical recommendations

• **Ideal:** Single treatment event (“big bang”)

When to use synthetic control:

- Get a good synthetic control for treatment unit
- If no good match exists in pre-period, stop (or adjust)
- **Better approach:** Ben-Michael, Feller & Rothstein (2021) adjust for imperfect pre-match

When to use synthetic DiD:

- Promising generalization for multiple treated units
- Key challenge: Convince readers why this works better than traditional DiD
- Recommendation: Show results with **both** DiD and synthetic DiD

Software packages:

- `augsynth`: Augmented synthetic control (Ben-Michael et al.)
- `synthdid`: Synthetic DiD (Arkhangelsky et al.)
- `tidysynth`: User-friendly synthetic control