

# diff - diff

v2.6

**What if treatment  
isn't binary?**

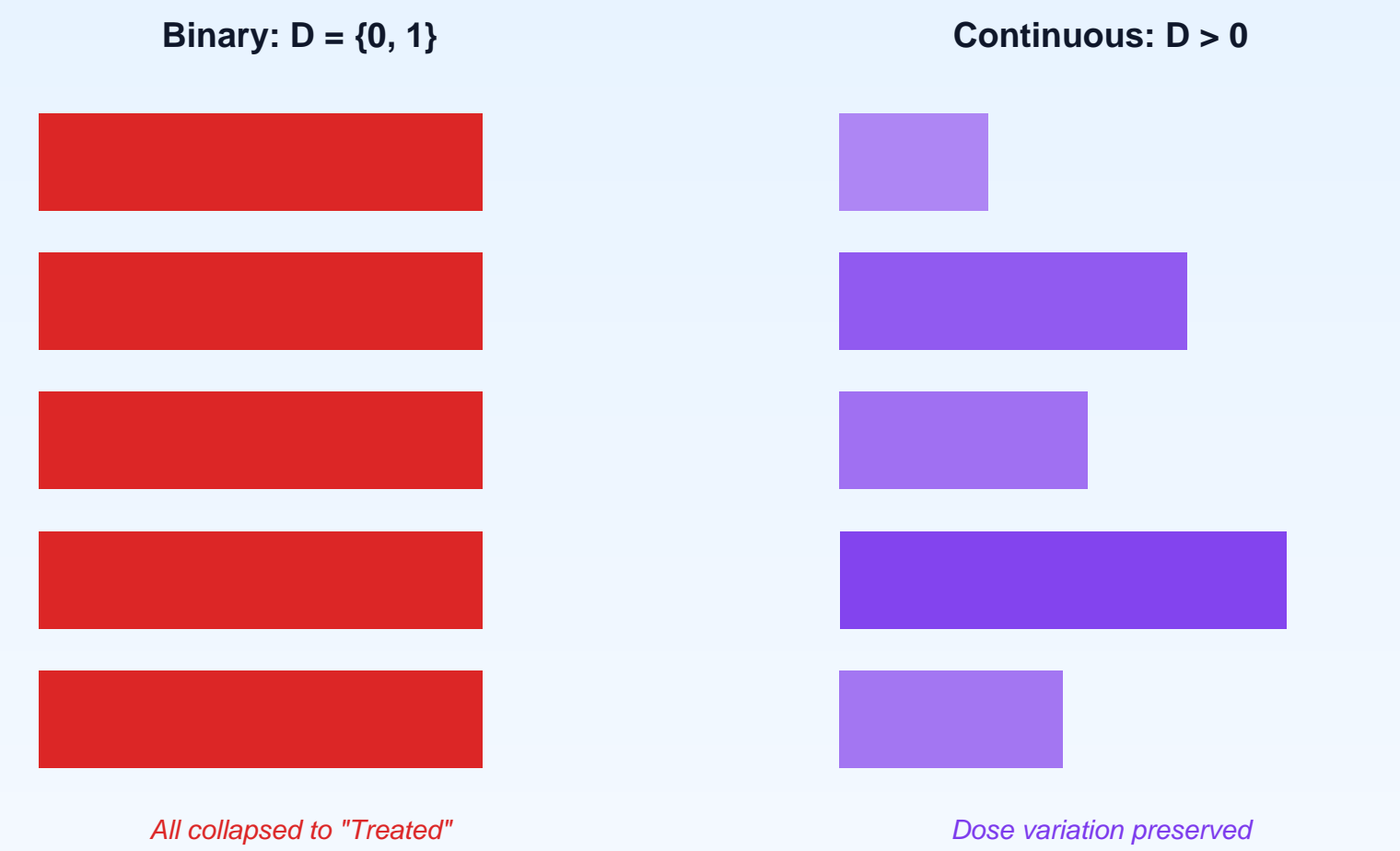
Dose-response curves for continuous treatments

Callaway, Goodman-Bacon & Sant'Anna (2024)

B-spline smoothing with analytical SEs

# Binary DiD

## Loses Information



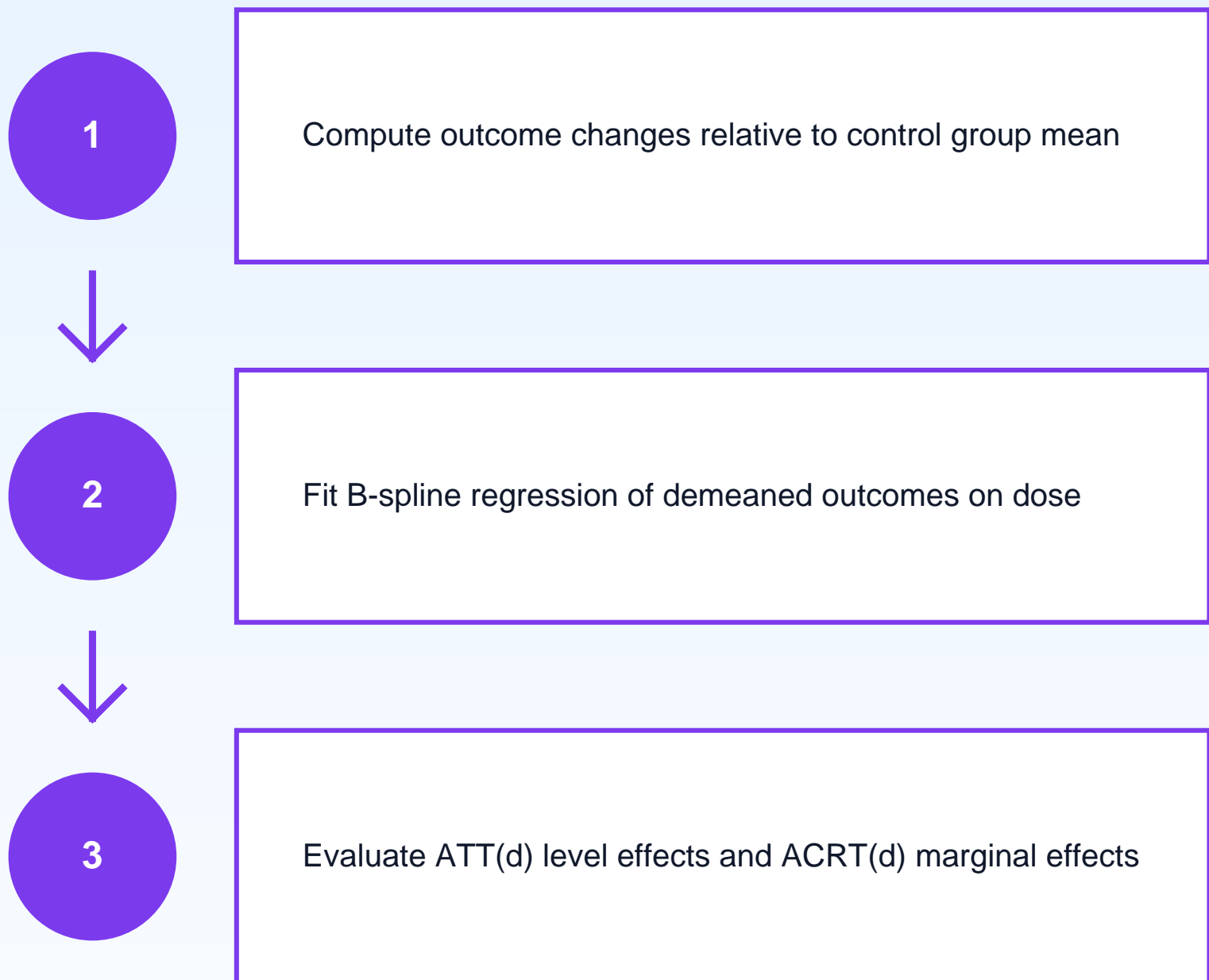
TWFE with a continuous treatment is biased --  
negative weights, contamination, and scale dependence.

Binarizing discards the dose-response relationship entirely

You need level effects AND marginal effects

# Continuous DiD

*Callaway, Goodman-Bacon & Sant'Anna (2024) | NBER WP 32117*



From binary to the full dose-response curve.

# The Math

Three targets, one estimation

B-Spline OLS

$$\Delta \tilde{Y}_i = \psi^K(D_i)' \beta + \varepsilon_i$$

*(demeaned outcome ~ B-spline basis of dose)*

ATT(d)

$$\text{ATT}(d) = \psi^K(d)' \hat{\beta}$$

*(level effect: total impact at dose d)*

ACRT(d)

$$\text{ACRT}(d) = \frac{\partial \psi^K(d)}{\partial d} \cdot \hat{\beta}$$

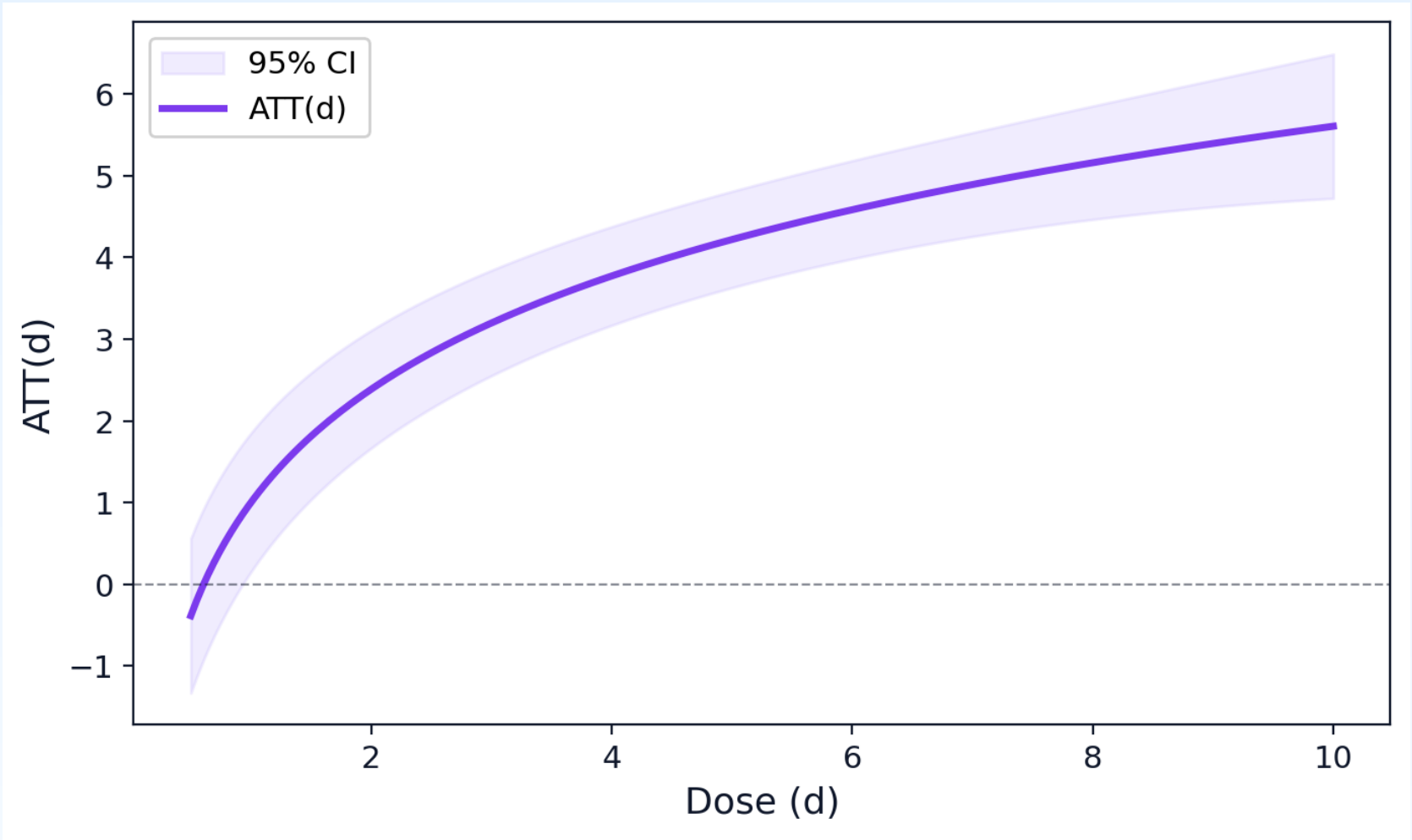
*(marginal effect: response per unit of dose)*

Influence-function SEs + multiplier bootstrap

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# Dose-Response

## Curve



**ATT(d): total impact at each dose level**

Confidence bands from influence functions or bootstrap

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# Two Questions

## One Estimator

### ATT(d)

#### Level Effect

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*What is the total impact  
at dose  $d$ ?*

A \$500 subsidy reduces  
emissions by 12 tons

### ACRT(d)

#### Marginal Effect

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*What is the return to one  
more unit of dose?*

Each additional \$100 reduces  
emissions by 1.8 tons

**Both are functions of  $d$  -- not just single numbers.**

Plus global summaries: overall ATT and overall ACRT

# What You Need to Believe

## Standard PT

### Parallel trends in untreated outcomes

**Identifies:**  $ATT(d|d)$  level effects within each dose group

Counterfactual trends are the same across  
all dose groups and the untreated.

## Strong PT

### No selection into dose based on effects

**Identifies:**  $ATT(d) + ACRT(d)$  dose-response curves

Units don't choose their dose based on  
how much they would benefit from it.

Note: Under standard PT, the slope of the dose-response  
curve does NOT identify the causal marginal effect.

# Drop-in

## API

```
from diff_diff import ContinuousDiD

est = ContinuousDiD(seed=42)

results = est.fit(

    data,

    outcome='outcome',

    unit='unit',

    time='period',

    first_treat='first_treat',

    dose='dose',

    aggregate='dose',

)

results.overall_att      # level effect

results.overall_acrt     # marginal effect
```

Same fit() API as every other diff-diff estimator.

Full walkthrough in Tutorial 14: Continuous DiD



# Where Dose Matters

## Job Training

Training hours as dose. How do earnings respond to each hour?

## Minimum Wage

Different increases across states.  
Employment effect per dollar?

## Subsidies

Varying grant amounts. What is the marginal return to spending?

## Pollution Exposure

Distance from source as dose.  
How does health vary with proximity?

Any setting where treatment intensity varies across units.

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# Every Method

## You Need

### Basic DiD / TWFE

Classic 2x2 and panel

### Sun-Abraham

Interaction-weighted (2021)

### Two-Stage DiD

Gardner (2022)

### Continuous DiD [NEW]

Callaway et al. (2024)

### Triple Difference

DDD with proper covariates

### Callaway-Sant'Anna

Staggered adoption (2021)

### Imputation DiD

Borusyak et al. (2024)

### Stacked DiD

Wing et al. (2024)

### Synthetic DiD

Arkhangelsky et al. (2021)

### Honest DiD

Rambachan-Roth sensitivity

### Bacon Decomposition

TWFE diagnostic weights

The most complete DiD toolkit in any language.

**diff-diff**

# Upgrade to

## v2.6

```
$ pip install --upgrade diff-diff
```

[github.com/igerber/diff-diff](https://github.com/igerber/diff-diff)

Full documentation & 14 tutorials included

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## diff - diff

Difference-in-Differences for Python