Online Appendix to Two-stage Differences in Differences

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Abstract

This document contains appendix material for Gardner et al. (2024).

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A Stata syntax

Suppose that `y` refers to the outcome, `year` the year, `id` the group, and `d` treatment status. The two-stage difference-in-differences estimator can be obtained, along with valid cluster-robust asymptotic standard errors, via GMM using the single Stata command:

```
gmm (eq1: (y - {xb: i.year} - {xg: ibn.id})*(1-d)) ///
  (eq2: y - {xb:} - {xg:} - {delta}*d), ///
  instruments(eq1: i.year ibn.id) ///
  instruments(eq2: d) winitial(identity) ///
  onestep quickderivatives vce(cluster id)
```

Variations on the two-stage estimator (such as the the two-stage event-study estimator) can be obtained using similar syntax. The `did2s` package (Butts, 2021) implements the same procedure more efficiently and scales more easily with individual fixed effects.

B Proofs

Derivation of Equation (3). From Equation (1), we can write

$$Y_{gpit} = \lambda_g + \alpha_p + \sum_{h=1}^{G}\sum_{q=h}^{P} \beta_{hq} 1(h,q)_{gpit} + e_{gpit}, \tag{1}$$

where $1(h,q)_{gpit}$ is an indicator for whether observation (g,p,i,t) corresponds to group h and period q, and $\mathbb{E}\left[e_{gpit} \,\middle|\, g, p, (1(h,q)_{gpit})\right] = 0$.

Let $\tilde{D}_{gp}$ denote the residual from a population regression of D_{gp} on group and period fixed effects. By the Frisch-Waugh-Lovell theorem, the coefficient on D_{gp} from a population regression of Y_{gpit} on D_{gp} and group and period effects is

$$\begin{aligned}
\beta^* &= \frac{\mathbb{E}\left[\tilde{D}_{gp} Y_{gpit})\right]}{\mathbb{E}\left[\tilde{D}_{gp}^2\right]} \\
&= \frac{\mathbb{E}\left[\tilde{D}_{gp} \sum_{h=1}^{G}\sum_{q=h}^{P} \beta_{hq} 1(h,q)_{gpit}\right]}{\mathbb{E}\left[\tilde{D}_{gp}^2\right]} \\
&= \sum_{h=1}^{G}\sum_{q=h}^{P} \frac{\mathbb{E}\left[\tilde{D}_{gp} 1(h,q)_{gpit}\right]\beta_{hq}}{\mathbb{E}\left[\tilde{D}_{gp}^2\right]} \\
&= \sum_{g=1}^{G}\sum_{p=g}^{P} \omega_{gp}\beta_{gp}.
\end{aligned}$$

where ω_{gp} is the coefficient from a regression of $1(h,q)_{gpit}$ on D_{gp} and group and period fixed effects. The second equality uses the facts that e_{gpit} is mean-independent of the regressors and that $\tilde{D}_{gp}$ is uncorrelated with group and period effects by construction.[1]

The weight ω_{gp} that difference in differences places on β_{gp} is the coefficient on D_{gp} from a regression of $1(g,p)_{gpit}$ on D_{gp} and group and period fixed effects. By the Frisch-Waugh-Lovell theorem, this is equivalent to the slope coefficient from a population regression of $1(g,p)_{gpit}$ on the residual from an auxiliary regression of D_{gp} on group and period effects. Using the two-way within or double-demeaned transformation, this residual can be expressed as

$$\tilde{D}_{gp} = [D_{gp} - \Pr(D_{gp} = 1 \,|\, g)] - [\Pr(D_{gp} = 1 \,|\, p) - \Pr(D_{gp} = 1)]. \tag{2}$$

[1]This, and the related result in Sun and Abraham (2021), can also be established by thinking of the term $\sum_{h=1}^{G}\sum_{q=h}^{P} \beta_{hq} 1(h,q)_{gpit}$ in Equation (1) as an omitted variable, and taking its projection onto the included regressors.

Since $\mathbb{E}\left[\tilde{D}_{gp}^2\right] = \mathbb{E}\left[\tilde{D}_{gp} D_{gp}\right]$, ω_{gp} can also be expressed as

$$\begin{aligned}
\omega_{gp} &= \frac{\mathbb{E}\left[1(g,p)_{gpit}\tilde{D}_{gp}\right]}{\operatorname{Var}\left[\tilde{D}_{gp}\right]} \\
&= \frac{\mathbb{E}\left[\tilde{D}_{gp} \,\middle|\, 1(g,p)_{gpit} = 1\right] \Pr\big(1(g,p)_{gpit} = 1\big)}{\mathbb{E}\left[\tilde{D}_{gp} \,\middle|\, D_{gp} = 1\right] \Pr\big(D_{gp} = 1\big)} \\
&= \frac{\left[1 - \Pr\big(D_{gp} = 1 \,|\, g\big) - \big(\Pr\big(D_{gp} = 1 \,|\, p\big) - \Pr\big(D_{gp} = 1\big)\big)\right] \Pr(g,p)}{\sum_{g'=1}^{G} \sum_{p'=g'}^{P} \left[1 - \Pr\big(D_{g'p'} = 1 \,|\, g'\big) - \big(\Pr\big(D_{g'p'} = 1 \,|\, p'\big) - \Pr\big(D_{g'p'} = 1\big)\big)\right] \Pr(g',p')},
\end{aligned}$$

where the final equality uses Equation (2). □

Lemma B.1. *Under Assumptions 1 and 2, $\hat{\gamma} \xrightarrow{p} \gamma$ and $\hat{\beta} \xrightarrow{p} \beta$.*

Proof of Lemma B.1. We have

$$\tilde{Y}_{0i} - \tilde{X}_{0i}\gamma = \begin{bmatrix} (\tilde{\varepsilon}_{i1})(1 - D_{i1}) \\ \vdots \\ (\tilde{\varepsilon}_{iT})(1 - D_{iT}) \end{bmatrix} =: \tilde{\varepsilon}_{0i}.$$

Hence,

$$\hat{\gamma} = \gamma + \left(\frac{1}{N}\sum_i \tilde{X}_{0i}'\tilde{X}_{0i}\right)^{-1} \left(\frac{1}{N}\sum_i \tilde{X}_{0i}'\tilde{\varepsilon}_{0i}\right).$$

Due to Assumption 1.3, and the existence of second moments in Assumption 2.2, by the weak law of large numbers (WLLN), $\frac{1}{N}\sum_i \tilde{X}_{0i}'\tilde{X}_{0i} \xrightarrow{p} \mathbb{E}\left[\tilde{X}_{0i}'\tilde{X}_{0i}\right]$. With Assumption 1.1 on correct specification and the WLLN, $\mathbb{E}\left[\tilde{X}_{0i}'\tilde{\varepsilon}_{0i}\right] = 0$. Hence, $\frac{1}{N}\sum_i \tilde{X}_{0i}'\tilde{\varepsilon}_{0i} \xrightarrow{p} 0$. Then, since $\mathbb{E}\left[\tilde{X}_{0i}'\tilde{X}_{0i}\right]$ is invertible by Assumption 2.2, by the continuous mapping theorem, $\hat{\gamma} \xrightarrow{p} \gamma$.

The OLS estimator is:

$$\begin{aligned}
\hat{\beta} &= \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\left(\tilde{Y}_{it} - \tilde{X}_{it}\hat{\gamma}\right)\right) \\
&= \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\left(\beta_{it}D_{it} + \tilde{\varepsilon}_{it} - \tilde{X}_{it}'(\hat{\gamma} - \gamma)\right)\right) \\
&= \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\beta_{it}\right) + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\left(\tilde{\varepsilon}_{it} - \tilde{X}_{it}'(\hat{\gamma} - \gamma)\right)\right).
\end{aligned}$$

It can be shown that $\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\beta_{it}\right) - \beta \xrightarrow{p} 0$. Since $\beta = E[\beta_{it} \mid$

$D_{it} = 1] = E[D_{it}\beta_{it}]/\Pr(D_{it} = 1)$,

$$\begin{aligned}
&\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\beta_{it}\right) - \beta \\
&= \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\beta_{it}\right) - \frac{E[D_{it}\beta_{it}]}{\Pr(D_{it} = 1)} = o_P(1).
\end{aligned}$$

Due to Assumptions 2.1 and 2.2, $\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\tilde{X}_{it}\right) = O_P(1)$ is bounded in probability, so, using the first-stage consistency result that $\hat{\gamma} \xrightarrow{p} \gamma$,

$$\begin{aligned}
\hat{\beta} &= \beta + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\left(\tilde{\varepsilon}_{it} - \tilde{X}_{it}'\left(\hat{\gamma} - \gamma\right)\right)\right) + o_P(1) \\
&= \beta + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\tilde{\varepsilon}_{it}\right) + o_P(1).
\end{aligned}$$

Due to Assumptions 1.2 and 1.3, $\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it} \xrightarrow{p} \Sigma_D > 0$. $D_{it}\tilde{\varepsilon}_{it}$ are also independent over individuals. Using a similar argument as before, $\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\tilde{\varepsilon}_{it} \xrightarrow{p} 0$. Then, $\hat{\beta} = \beta + o_P(1)$ as required. □

Proof of Theorem 1. If the conditions of Theorem 6.1 of Newey and McFadden (1994) are satisfied, the result automatically follows. Hence, the proof verifies its conditions. Due to Lemma B.1, we already have $\hat{\gamma} \xrightarrow{p} \gamma$ and $\hat{\beta} \xrightarrow{p} \beta$, fulfilling the probability limit requirement. Next, we want to show the following:

1. β is in the interior of the parameter space.
2. $g(Z; \gamma, \beta)$ is continuously differentiable around β.
3. $\mathbb{E}[g(Z; \gamma, \beta)] = 0$ and $\mathbb{E}\left[\|g(Z; \gamma, \beta)\|^2\right]$ is finite.
4. $\mathbb{E}\left[\sup_{(\gamma,\beta)} \|\nabla g(Z; \gamma, \beta)\|\right] < \infty$, where $\nabla g(Z; \gamma, \beta)$ is the derivative of g with respect to (γ', β).
5. $\mathbb{E}[\nabla g(Z; \gamma, \beta)]'\mathbb{E}[\nabla g(Z; \gamma, \beta)]$ is nonsingular.
6. $\frac{1}{N}\sum_{i=1}^{N} g\left(Z_i; \hat{\gamma}, \beta\right) \xrightarrow{p} 0$ and $\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\tilde{X}_{0i}'\left(\tilde{Y}_{0i} - \tilde{X}_{0i}\gamma\right)\right) \xrightarrow{p} 0$.

Condition 1 is straightforward as long as no further constraints are imposed on β, which is true in the setting. For condition 2, observe that $\nabla_\beta g(Z; \gamma, \beta) = -\sum_t D_t$, which is continuously differentiable. For condition 3, $\mathbb{E}[g(Z; \gamma, \beta)] = 0$ is immediate by assumption, and we have

$$\begin{aligned}
\mathbb{E}\left[\|g(Z; \gamma, \beta)\|^2\right] &= \mathbb{E}\left[\left(\sum_{t=1}^{T} D_{it}\left(\tilde{Y}_{it} - \tilde{X}_{it}'\gamma - D_{it}\beta\right)\right)^2\right] \\
&= \mathbb{E}\left[\left(\sum_{t=1}^{T}\left[\tilde{\varepsilon}_{it} + \left(\beta_{it} - \beta\right)D_{it}\right]D_{it}\right)^2\right] < \infty
\end{aligned}$$

due to Assumption 2.1 giving those objects finite moments and T being finite due to Assumption 1.4. Condition 4 is immediate from finite moments, and condition 5 is immediate from Assumption 1.2. For condition 6,

$$\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N} g(Z_i;\hat{\gamma},\beta) &= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} D_{it}\left(\tilde{Y}_{it}-\tilde{X}_{it}\hat{\gamma}-D_{it}\beta\right) \\
&= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\beta_{it}D_{it}+\tilde{\varepsilon}_{it}-\tilde{X}_{it}'\left(\hat{\gamma}-\gamma\right)-D_{it}\beta\right]D_{it} \\
&= \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\tilde{\varepsilon}_{it}-\tilde{X}_{it}'\left(\hat{\gamma}-\gamma\right)+\left(\beta_{it}-\beta\right)D_{it}\right]D_{it} = o_P(1)
\end{aligned}$$

due to previous arguments. Finally, the second part of condition 6 is immediate from the WLLN. ☐

Lemma B.2.

$$\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W_{it}'\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W_{it}'\eta_{it}\right) = \begin{bmatrix} \frac{1}{N_{-\underline{R}}}\sum_{i=1}^{N}\sum_{t=1}^{T} 1\left[t-t^*(i)=-\underline{R}\right]\eta_{-\underline{R}it} \\ \vdots \\ \frac{1}{N_{\overline{R}}}\sum_{i=1}^{N}\sum_{t=1}^{T} 1\left[t-t^*(i)=\overline{R}\right]\eta_{\overline{R}it} \end{bmatrix}.$$

Proof of Lemma B.2.

$$\begin{aligned}
\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W_{it}' &= \sum_{i=1}^{N}\sum_{t=1}^{T}\begin{bmatrix} 1\left[t-t^*(i)=-\underline{R}\right] \\ \vdots \\ 1\left[t-t^*(i)=\overline{R}\right]\end{bmatrix}\begin{bmatrix} 1\left[t-t^*(i)=-\underline{R}\right] \\ \vdots \\ 1\left[t-t^*(i)=\overline{R}\right]\end{bmatrix}' \\
&= \sum_{i=1}^{N}\sum_{t=1}^{T}\operatorname{diag}\left(1\left[t-t^*(i)=-\underline{R}\right],\cdots,1\left[t-t^*(i)=\overline{R}\right]\right) \\
&= \operatorname{diag}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}1\left[t-t^*(i)=-\underline{R}\right],\cdots,\sum_{i=1}^{N}\sum_{t=1}^{T}1\left[t-t^*(i)=\overline{R}\right]\right) \\
&= \operatorname{diag}\left(N_{\underline{R}},\cdots,N_{\overline{R}}\right).
\end{aligned}$$

Similarly,

$$\begin{aligned}
\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W_{it}'\eta_{it} &= \sum_{i=1}^{N}\sum_{t=1}^{T}\operatorname{diag}\left(1\left[t-t^*(i)=-\underline{R}\right],\cdots,1\left[t-t^*(i)=\overline{R}\right]\right)\eta_{it} \\
&= \begin{bmatrix} \sum_{i=1}^{N}\sum_{t=1}^{T} 1\left[t-t^*(i)=-\underline{R}\right]\eta_{-\underline{R}it} \\ \vdots \\ \sum_{i=1}^{N}\sum_{t=1}^{T} 1\left[t-t^*(i)=-\underline{R}\right]\eta_{\overline{R}it}\end{bmatrix}.
\end{aligned}$$

☐

Proof of Theorem 2. The proof is analogous to that of 2SDD. The first-stage regression then yields:

$$\hat{\gamma} = \gamma + \left(\frac{1}{N}\sum_{i}\tilde{X}_{Qi}'\tilde{X}_{Qi}\right)^{-1}\left(\frac{1}{N}\sum_{i}\tilde{X}_{Qi}'\tilde{\varepsilon}_{Qi}\right).$$

Due to Assumption 1.3, and the existence of second moments in Assumption 3.2, by the weak law of large numbers (WLLN), $\frac{1}{N}\sum_i \tilde{X}'_{Qi}\tilde{X}_{Qi} \xrightarrow{p} \mathbb{E}\left[\tilde{X}'_{Qi}\tilde{X}_{Qi}\right]$. Similarly, $\frac{1}{N}\sum_i \tilde{X}'_{Qi}\tilde{\varepsilon}_{Qi} \xrightarrow{p} 0$ and $\hat{\gamma} \xrightarrow{p} \gamma$. We can express the estimated coefficient $\hat{\eta}$ as:

$$\hat{\eta} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\eta_{it}\right) + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}\left(\tilde{\varepsilon}_{it} + \tilde{X}_{it}\left(\hat{\gamma}-\gamma\right)\right)\right).$$

Due to an argument similar to the proof of Theorem 1, $\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\eta_{it}\right) \xrightarrow{p} \eta$. Due to Assumption 3.2, $\left|\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}\tilde{X}_{it}\right)\right|$ is bounded in probability, so

$$\begin{aligned}\hat{\eta} &= \eta + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}\left(\tilde{\varepsilon}_{it} - \tilde{X}'_{it}\left(\hat{\gamma}-\gamma\right)\right)\right) + o_P(1)\\ &= \eta + \left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}\tilde{\varepsilon}_{it}\right) + o_P(1).\end{aligned}$$

The first equality occurs due to Lemma B.2. Due to Assumption 1.3, $\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}W'_{it} \to \mathbb{E}\left[\operatorname{diag}\left(N_{i,-\underline{R}}, \cdots, N_{i,\overline{R}}\right)\right] =: \Sigma_W$.

Due to Assumption 3.3, Σ_W is invertible and finite. $\sum_{t=1}^{T} W_{it}\tilde{\varepsilon}_{it}$ are also independent over individuals. Due to finite moments, we can apply the law of large numbers to obtain $\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T} W_{it}\tilde{\varepsilon}_{it} \xrightarrow{p} 0$. Then, $\hat{\eta} = \eta + o_P(1)$ as required.

If the conditions of Theorem 6.1 of Newey and McFadden (1994) are satisfied, the result automatically follows. Verifying the conditions is analogous to the proof of Theorem 1.

□

C Simulations: Random design vs. fixed design

We discuss how our simulation environment compares to that of Borusyak, Jaravel and Spiess (2024), who propose a numerically equivalent estimator with a different asymptotic theory. They propose an asymptotically conservative approach to inference and document that it performs well in finite samples using a series of Monte Carlo simulations. As our discussion of overfitting in Section 4.2.2 highlights, we observe substantial rates of over-rejection using their variance estimator, particularly when treatment timing varies over longer periods.

Furthermore, their simulation environment, and their theory more generally, interprets treatment assignment and event times as non-stochastic. The design—treated states, treatment effects, and treatment timing—is therefore held fixed, and the source of randomness across simulations is the randomly drawn error term for generating outcomes. With the error term in outcomes as the sole source of randomness, the variance of that error term plays a crucial role.

We explore the conditions under which rejection rates can reach 100% in such a setup. A simple example with two periods and two states suffices to illustrate the problems that can arise for a small error term variance. Consider a placebo law, for which the true effect is zero, that applies to a random sample of treated states. In the absence of any true treatment effect, we would expect changes in outcomes for both treated and control states to be similar, and any observed discrepancy between the changes for the two groups would be solely attributed to the random error term. However, a finite difference in outcomes arises because the assignment of states to treatment or control groups is fixed after being drawn only once. This finite difference is not fully absorbed by state and year fixed effects, leading to misspecification. As a result, when the variance of the error term is sufficiently small compared to that finite difference, we observe consistent rejection of the null hypothesis. Assuming a larger error variance, using a large sample of treated states, or using random designs mitigates this issue (and we verify that our conclusions regarding the performance of the various estimators continue to hold under fixed designs with large error variance). Our discussion highlights the conceptual appeal of adopting a "random design" approach, in which stochasticity is incorporated into the simulation by randomly drawing treated states, treatment effects, and treatment timing in each iteration. Under random designs, even with a small error variance, rejection rates remain accurate and avoid spurious over-rejection.

D Empirical applications

D.1 Selection of papers and outcomes

Below is the list of papers included in our empirical analysis, which appear in Table 1 of Sun and Abraham (2021), and the outcomes they study. We omit outcomes that are unavailable in the replication data, or are too slow to run (more than 5 days of runtime) for at least one of the methods.

- Bailey and Goodman-Bacon (2015)
  - Age-adjusted mortality rate (Figure 5)
  - Infant mortality rate (Figure 7.A)
  - Age-adjusted mortality rate: children (1–14) (Figure 7.B)
  - Age-adjusted mortality rate: adults (15–49) (Figure 7.C)
  - Age-adjusted mortality rate: older adults (50+) (Figure 7.D)
- Deryugina (2017)
  - Effect of a hurricane on earnings and transfers (Figure 2)
  - Effect of a hurricane on demographics (Figure 3)
  - Effect of a hurricane on transfer components (Figures 4 and 5)
- He and Wang (2017)
  - Subsidized population (Figure 2.A)
  - Poor-quality housing (Figure 2.B)
  - Registered poor households (Figure 2.C)
  - People with disabilities (Figure 2.D)
- Kuziemko, Meckel and Rossin-Slater (2018)
  - Mortality rates of children born to US-born Black mothers (Figure 2.A)
  - Mortality rates of children born to US-born Hispanic mothers (Figure 2.B)
- Lafortune, Rothstein and Schanzenbach (2018)
  - Mean state revenues in lowest income districts (Figure 3)
  - Mean state revenues in highest income districts (Figure 4)
  - Progressivity of state revenues (Figure 5)
  - Mean total revenues per pupil (Figure A3(a))

  - Mean total revenues per pupil in the lowest income quintile of districts (Figure A3(b))
  - Mean total revenues per pupil in the highest income quintile of districts (Figure A3(c))
  - Difference in mean total revenues per pupil between top and bottom quintile districts (Figure A3(d))

- Tewari (2014)
  - Home ownership (Figure 1)

- Ujhelyi (2014)
  - Share of intergovernmental expenditures in total expenditures (Figure 1)

D.2 Replication of Kuziemko, Meckel and Rossin-Slater (2018)

The Kuziemko, Meckel and Rossin-Slater (2018) paper studies the effect of the transition from Medicaid's public fee-for-service (FFS) plan to private Medicaid Managed Care (MMC) plans on infant mortality rates for US-born Black and Hispanic mothers in Texas. Their analysis uses 250 counties in Texas, with 9 years of data from 1993 to 2001. Of the 250 counties, 3 are treated in 1995, 36 are treated in 1996, 1 is treated in 1997, 8 are treated in 1998, and 9 are treated in 1999.

The dataset contains the month and year in which each treated county switched from FFS to MMC. However, the authors estimate the effect of the transition on infant mortality rates using a two-way fixed effects specification with year-since-treatment event dummies, where years are defined as 12-month periods relative to the event time. We attempt to replicate the analysis of Kuziemko, Meckel and Rossin-Slater (2018) using this kind of specification with the heterogeneity-robust estimators.

The 2SDD approach is easily implemented by using month fixed effects in the first stage and year-since-treatment event dummies in the second stage. To obtain estimates using `csdid` (Rios-Avila, Sant'Anna and Callaway, 2023), `eventstudyinteract` (Sun, 2021), `did_multiplegt_dyn` (de Chaisemartin et al., 2023), and `jwdid` (Rios-Avila, Nagengast and Yotov, 2022), we must define the cohort as the treatment year (not the exact month) to obtain dynamic effects by year since treatment. We present these results in Appendix Figure 2. However, we note that the conceptually correct way to do this exercise using those estimators would be to estimate separate effects for each month and then aggregate them into 12-month bins. This process would be somewhat cumbersome, and if undertaken, would require either assuming the distribution of units in each bin is known, or using a bootstrap, or devising a potentially complicated analytical asymptotic adjustment to account for that uncertainty.

This highlights the flexibility and simplicity advantages of 2SDD. With 2SDD, implementing the conceptually correct approach is straightforward: Simply include month fixed effects in the first stage and years-since-treatment indicators in the second stage.[2]

[2] However, we were unable to obtain estimates using the imputation approach (Borusyak, 2021) when adding month fixed effects in the first stage.

E Extension to stacked differences in differences

In the stacked approach, a new dataset is created for each treated group, containing observations on that group $\overline{R}$ periods before, and $\bar{P}$ periods after, the treatment is adopted, as well as on units that are not yet treated during these periods. These group-specific datasets are stacked, and outcomes are regressed on treatment status and dataset-specific group and period fixed effects:

$$Y_{cgpit} = \lambda_{cg} + \lambda_{cp} + \beta D_{cgp} + \varepsilon_{cgpit},$$

where *cgpit* indexes the value of an observation in the dataset for group c for the ith member of group g during the tth time of period p.

Let D_{cgp} be an indicator for whether group g is treated during period p of the group-c dataset, and D_{rcgp} be an indicator for whether members of g have been treated for $r \in \{1, \dots, \bar{P}\}$ periods as of period p in dataset c. Let $\tau = \bar{P}/(\bar{P} + \overline{R} + 1)$ denote the fraction of periods during which treated units in any group-specific dataset are treated, π_c denote the fraction of units in dataset c that belong to the treatment group, and ρ_c denote size of the group-c dataset relative to the stacked dataset.

The weight ω_{rg} that stacked differences in differences places on the r-period average treatment effect β_{rg} for group g is given by the slope coefficient from a population regression of D_{rcgp} on the residual $\tilde{D}_{cgp}$ from a regression of D_{cgp} on dataset×period and dataset×group effects. This residual is

$$\tilde{D}_{cgp} = D_{cgp} - P(D_{cgp} = 1|g, c) - [P(D_{cgp} = 1|p, c) - P(D_{cgp} = 1|c)],$$

where statements conditional on c are true in the population corresponding to dataset c. Using this expression and adapting (3) to the stacked setting,

$$\begin{aligned}\omega_{rg} &= \frac{[1 - \tau - (\pi_c - \tau\pi_c)]P(D_{rcgp} = 1)}{\sum_{c=1}^{G} \sum_{p=1}^{\bar{P}} [1 - \tau - (\pi_c - \tau\pi_c)]P(D_{rcgp} = 1)} \\ &= \frac{(1 - \tau)(1 - \pi_c)\tau\pi_c\rho_c}{\sum_{c=1}^{G} \sum_{p=1}^{\bar{P}} (1 - \tau)(1 - \pi_c)\tau\pi_c\rho_c} \\ &= \frac{(1 - \pi_c)\pi_c\rho_c}{\bar{P} \sum_{c=1}^{G} (1 - \pi_c)\pi_c\rho_c}.\end{aligned}$$

References

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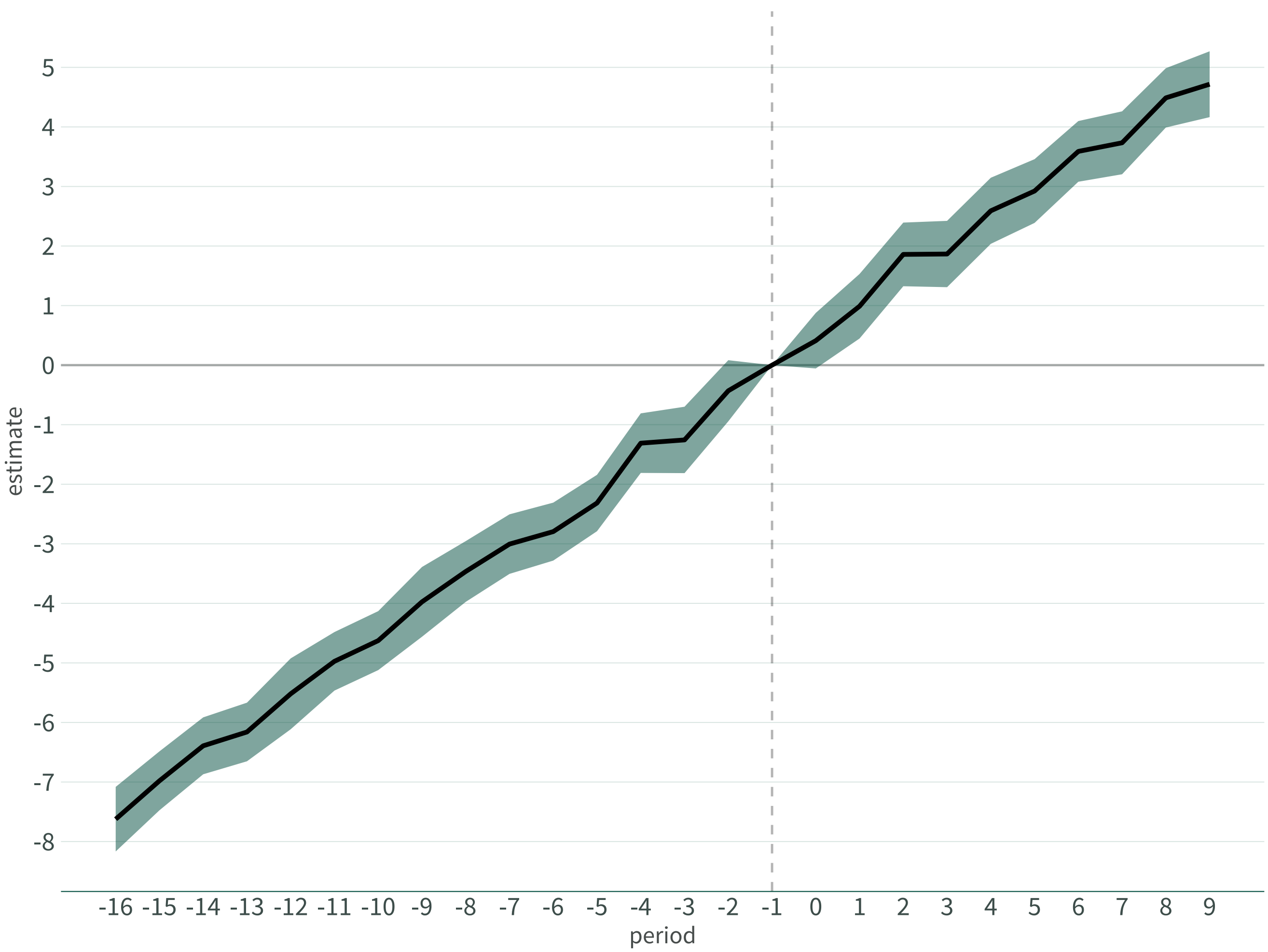
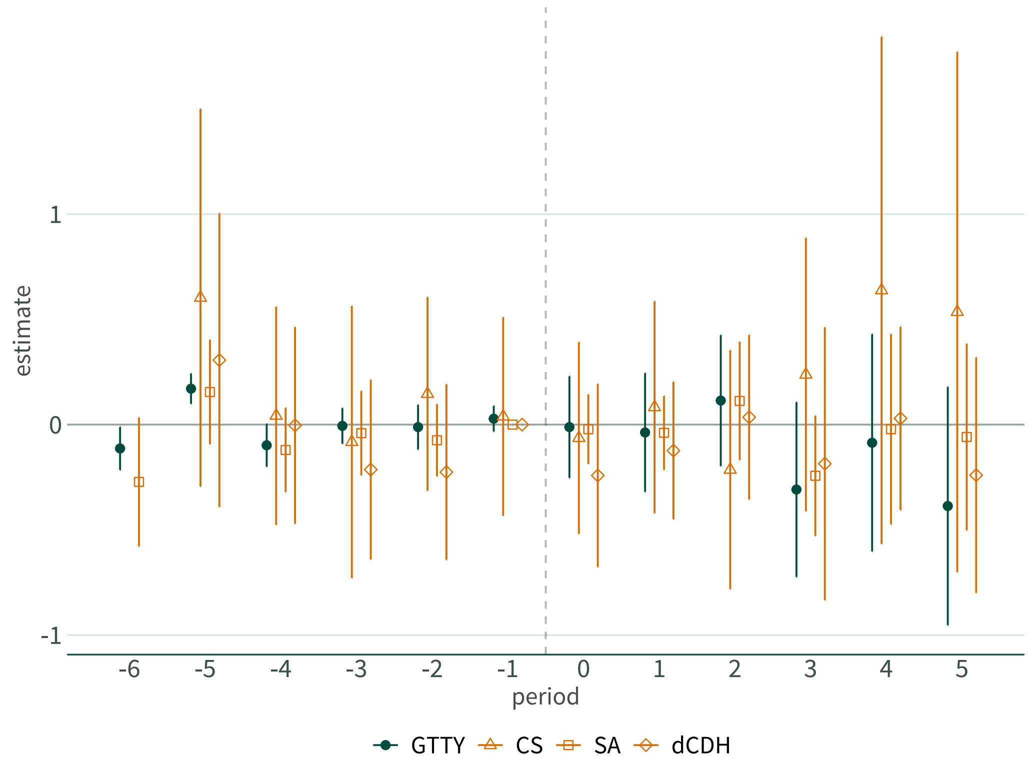
F Appendix Figures and Tables

Appendix Figure 1: Event-study in non-staggered setting with pre-trend

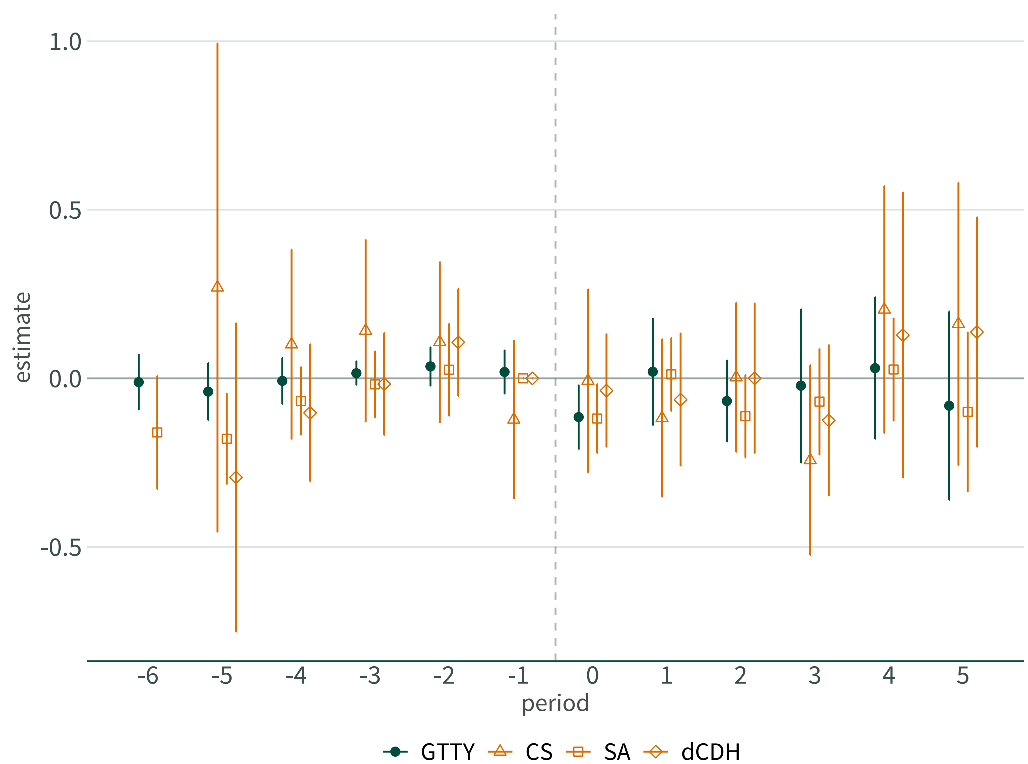


Note: This figure displays event-study estimates for a simulated dataset exhibiting a pre-trend from Roth (2024) by applying 2SDD with the first stage estimated using observations for eventually-treated units in the period immediately before they adopt the treatment as well as all observations for never-treated units. Under this data-generating process, the outcome for treated units follows a linear trend: $Y_{it} = 0.5 \cdot t \cdot D_i + \varepsilon_{it}$, where D_i is an indicator for treatment and ε_{it} are i.i.d. standard normal.

Appendix Figure 2: Empirical applications: Kuziemko, Meckel and Rossin-Slater (2018) event study estimates



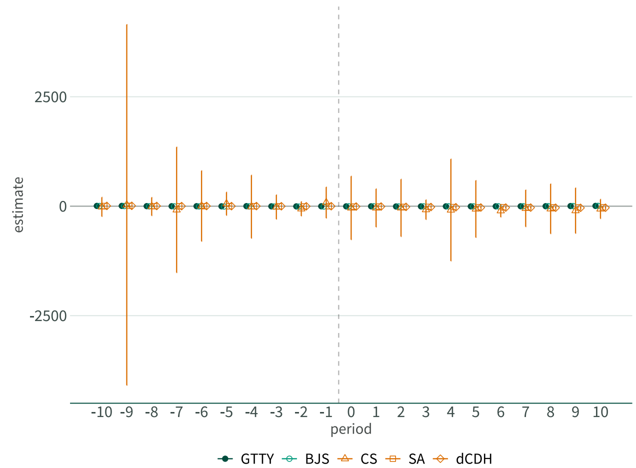
(a) Figure 2(a)



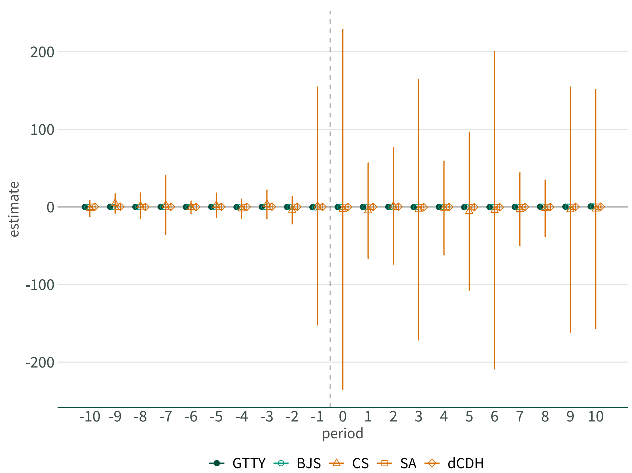
(b) Figure 2(b)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in Kuziemko, Meckel and Rossin-Slater (2018).

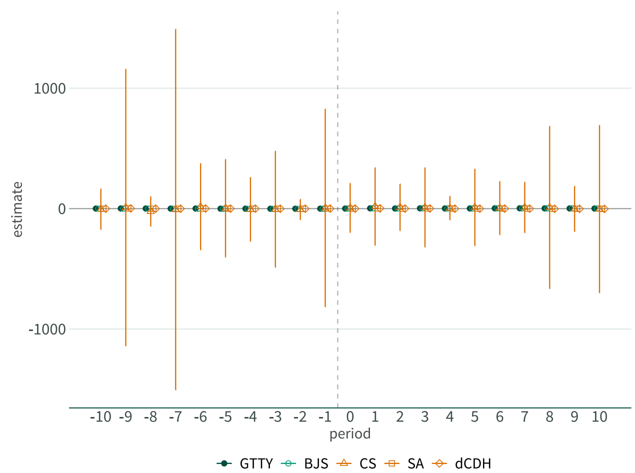
Appendix Figure 3: Empirical applications: Bailey and Goodman-Bacon (2015) event study estimates



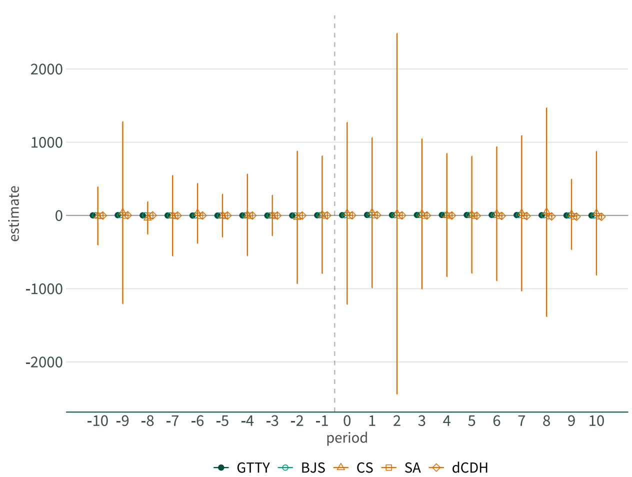
(a) Figure 5



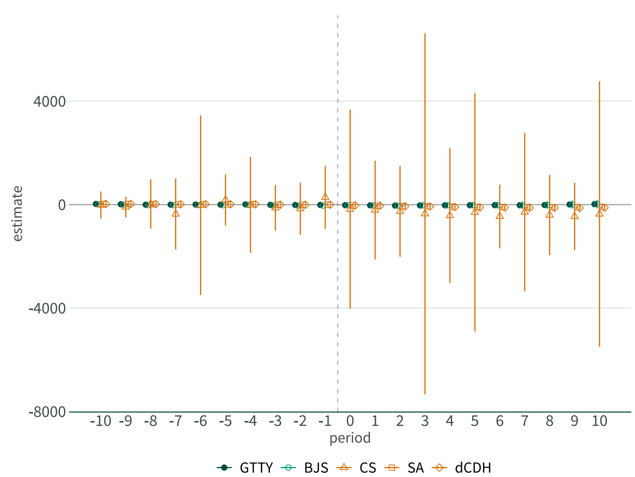
(b) Figure 7(a)



(c) Figure 7(b)



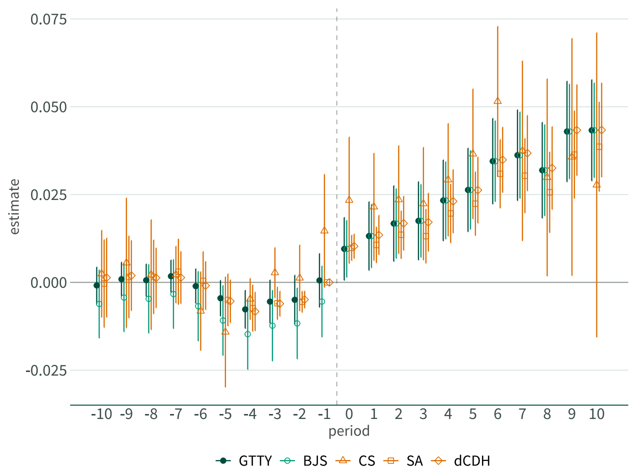
(d) Figure 7(c)



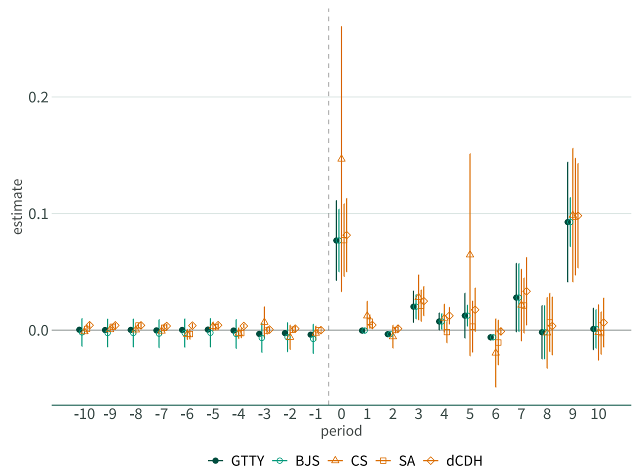
(e) Figure 7(d)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in Bailey and Goodman-Bacon (2015).

Appendix Figure 4: Empirical applications: Deryugina (2017) event study estimates (part 1)



(a) Figure 2(a)



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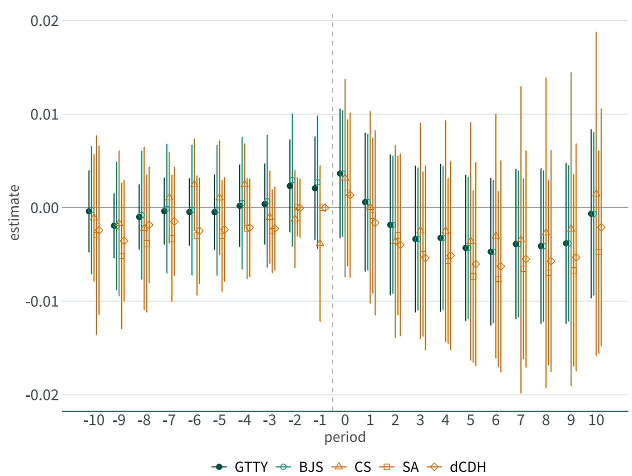
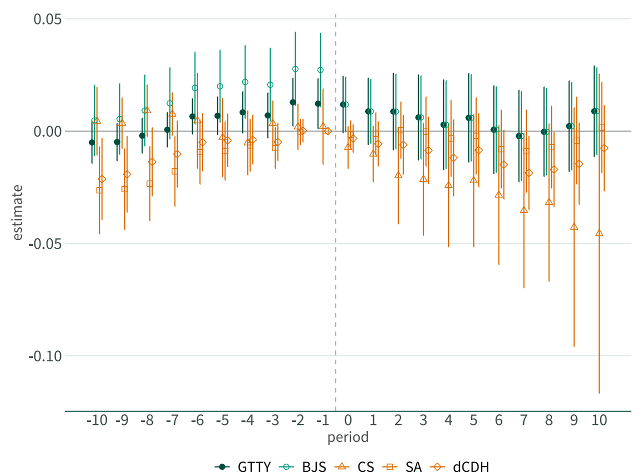
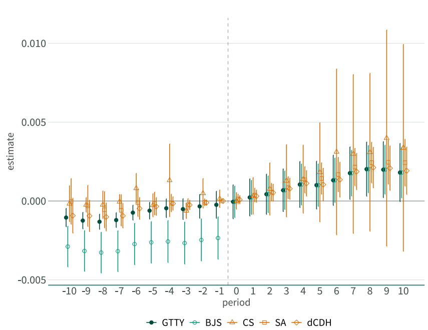


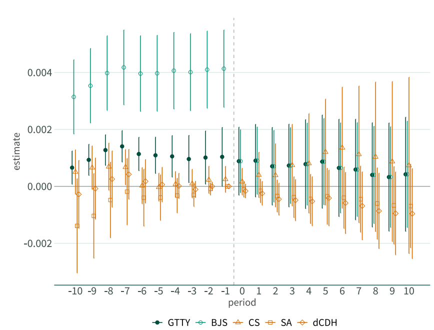
(c) Figure 2(c)



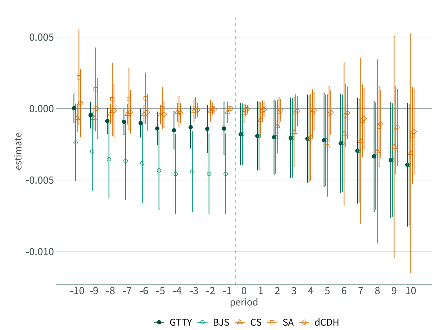
(d) Figure 2(d)



(e) Figure 3(b)



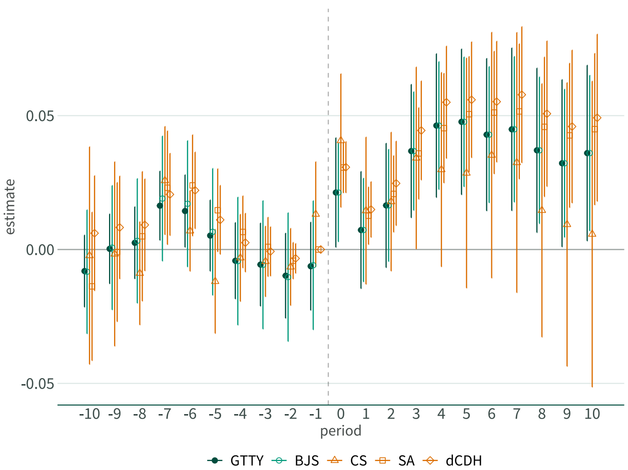
(f) Figure 3(c)



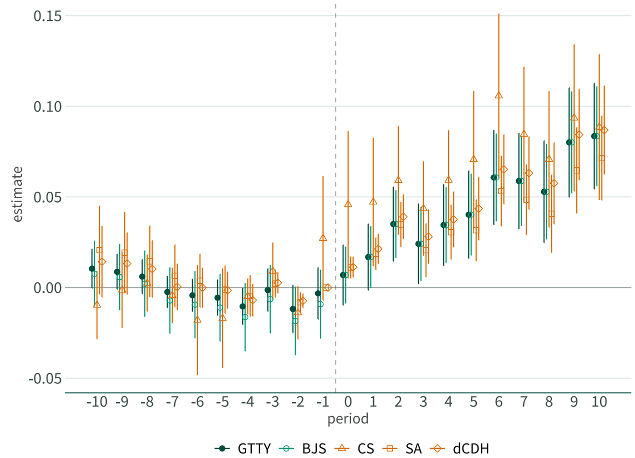
(g) Figure 3(d)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in Deryugina (2017); see Appendix Figure 5 for the remaining estimates.

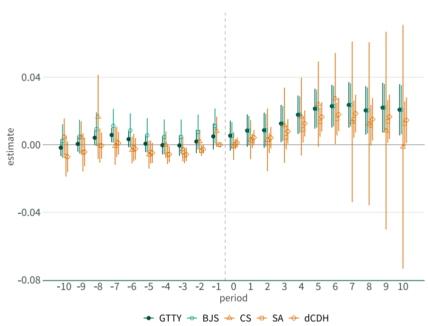
Appendix Figure 5: Empirical applications: Deryugina (2017) event study estimates (part 2)



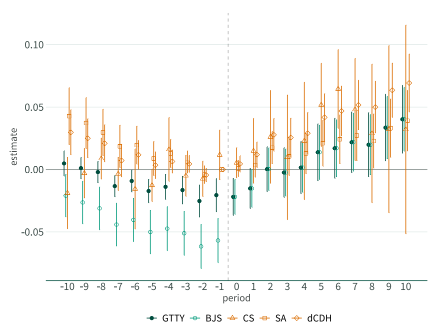
(a) Figure 4(a)



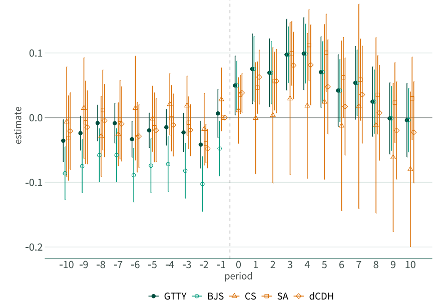
(b) Figure 4(b)



(c) Figure 4(c)



(d) Figure 4(d)



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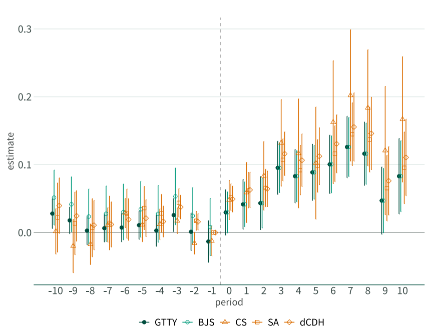

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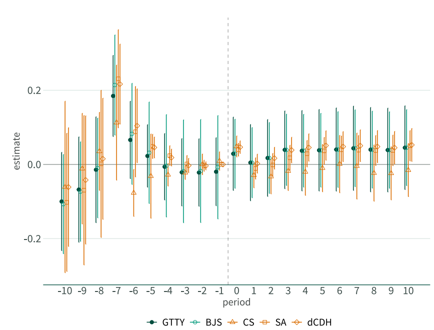

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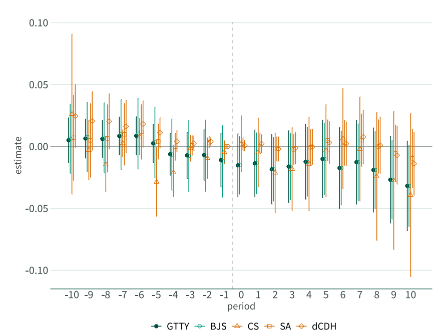
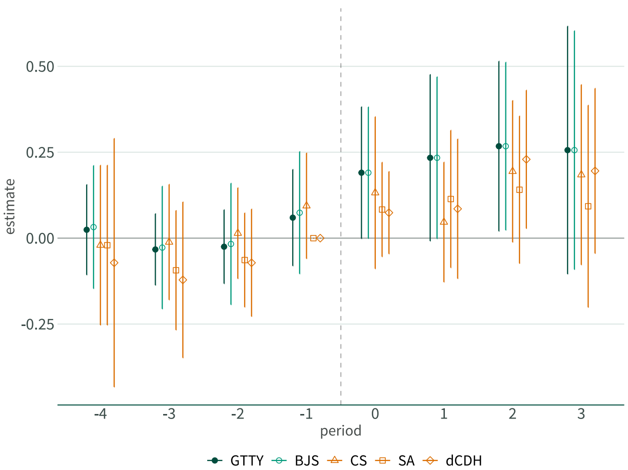


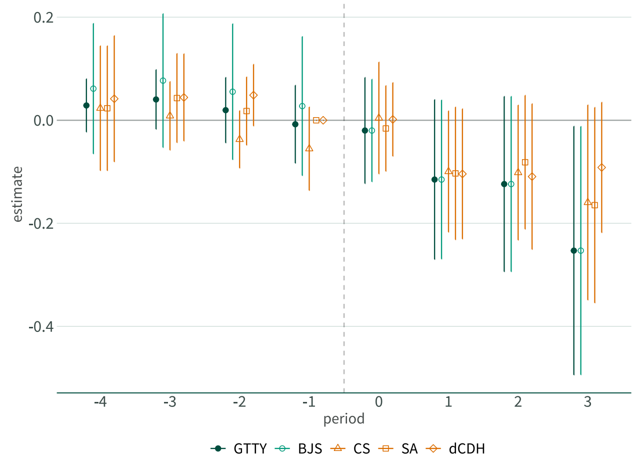
(h) Figure 5(d)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in Deryugina (2017); see Appendix Figure 4 for the remaining estimates.

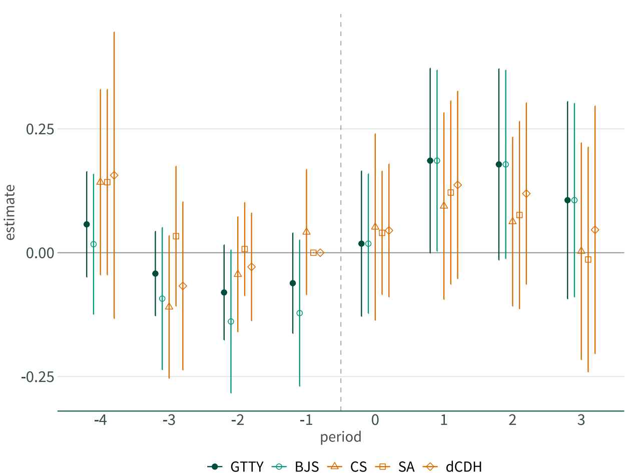
Appendix Figure 6: Empirical applications: He and Wang (2017) event study estimates



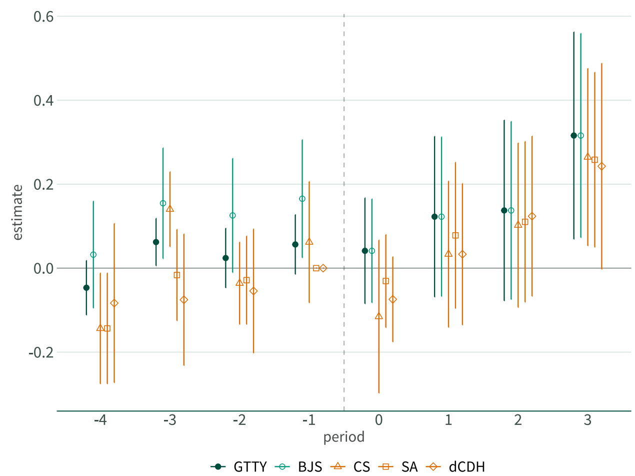
(a) Figure 2(a)



(b) Figure 2(b)



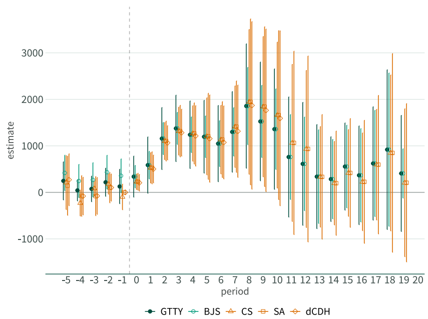
(c) Figure 2(c)



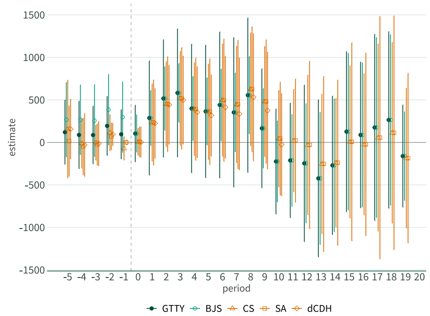
(d) Figure 2(d)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in He and Wang (2017).

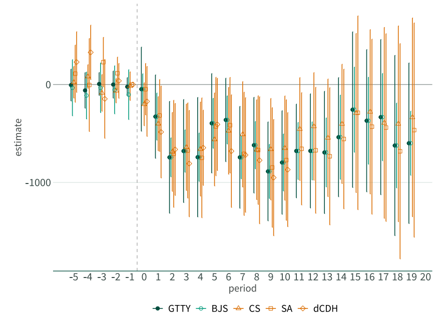
Appendix Figure 7: Empirical applications: Lafortune, Rothstein and Schanzenbach (2018) event study estimates



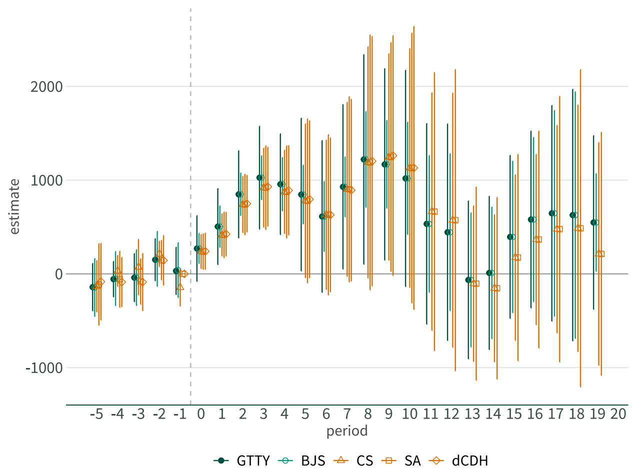
(a) Figure 3



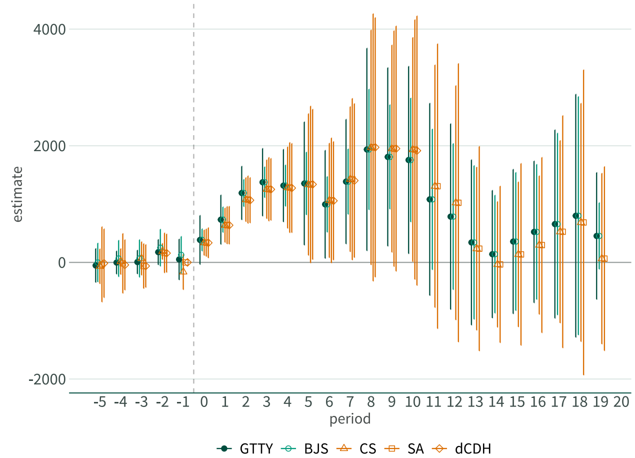
(b) Figure 4



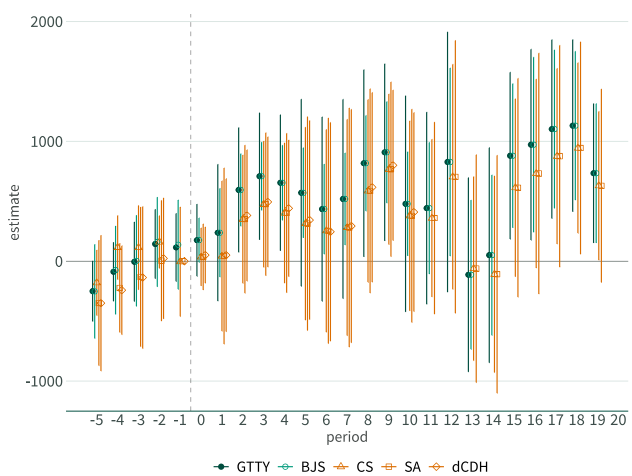
(c) Figure 5



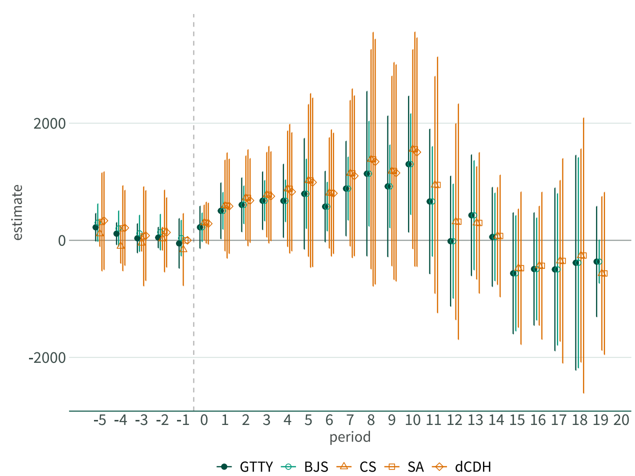
(d) Figure A.3(a)



(e) Figure A.3(b)



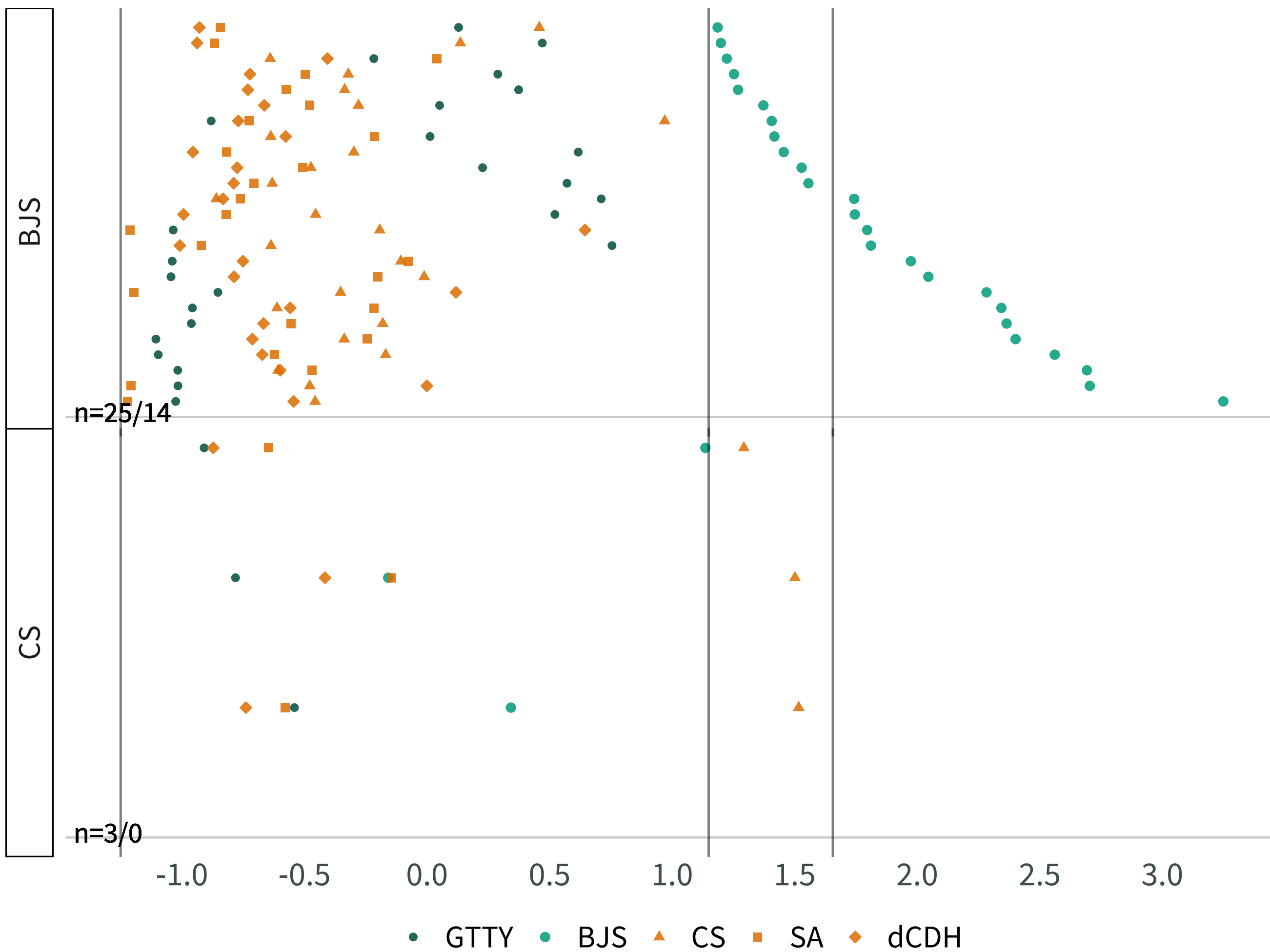
(f) Figure A.3(c)



(g) Figure A.3(d)

Note: This table reports event-study estimates from applying each estimator to the event-study specifications in Lafortune, Rothstein and Schanzenbach (2018).

Appendix Figure 8: Empirical applications: Outlier pre-treatment normalized standard error differences



Note: Among the five estimators we investigate, each panel of this figure corresponds to an estimator for which a standard error estimate (associated with a particular pre-treatment period before −1, outcome variable, and empirical setting) significantly deviates from the average of the other methods' standard errors. Each entry displays the difference between each method's standard error and its associated leave-out mean, normalized by the average of the absolute value of the standard errors for that coefficient. The criterion for determining that an estimator's standard error significantly deviates from that of the other estimators is that the normalized difference falls in the top 2.5 percent or bottom 2.5 percent of the distribution (vertical bars closer to zero as thresholds), excluding estimates from the Bailey and Goodman-Bacon (2015) paper. The numbers in the bottom left of each panel indicate the number of such outlier estimates at the 5 percent level and 1 percent level, respectively.

Appendix Table 1: Simulations (CPS wage data, heterogeneous treatment effects): 40 states treated over 20 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.99	0.1036	0.0018	0.1046	0.08
	1	5.39	0.1041	-0.0026	0.1019	
	2	4.99	0.1041	-0.0021	0.1046	
	3	4.99	0.1060	0.0003	0.1013	
	4	5.39	0.1057	-0.0027	0.1072	
BJS	0	15.97	0.0756	-0.0036	0.1004	0.25
	1	16.17	0.0767	0.0067	0.1066	
	2	13.97	0.0767	0.0005	0.0996	
	3	16.97	0.0768	0.0092	0.1065	
	4	16.37	0.0774	0.0029	0.1082	
CS	0	6.19	0.1451	0.0012	0.1470	27.36
	1	4.19	0.1464	-0.0036	0.1425	
	2	5.19	0.1460	0.0023	0.1451	
	3	5.79	0.1459	0.0041	0.1478	
	4	4.79	0.1461	0.0021	0.1427	
SA	0	1.40	0.1707	0.0125	0.1362	48.63
	1	1.40	0.1716	0.0090	0.1336	
	2	1.40	0.1708	0.0064	0.1348	
	3	1.40	0.1726	0.0120	0.1349	
	4	2.79	0.1726	0.0073	0.1437	
dCDH	0	6.79	0.1279	0.0141	0.1347	3.70
	1	8.18	0.1272	0.0098	0.1324	
	2	7.98	0.1280	0.0104	0.1373	
	3	5.99	0.1287	0.0127	0.1356	
	4	7.78	0.1294	0.0103	0.1415	
W	0	4.99	0.1404	0.0135	0.1373	87.79
	1	4.99	0.1403	0.0101	0.1340	
	2	4.99	0.1404	0.0074	0.1357	
	3	5.19	0.1415	0.0129	0.1360	
	4	5.79	0.1420	0.0084	0.1428	

Note: The table reports results from 501 simulations of 40 treated states over 20 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 2: Simulations (CPS wage data, heterogeneous treatment effects): 40 states treated over 15 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.79	0.1047	0.0006	0.1074	0.10
	1	6.79	0.1050	0.0013	0.1064	
	2	6.19	0.1063	0.0026	0.1094	
	3	5.19	0.1057	-0.0002	0.1024	
	4	4.39	0.1075	0.0014	0.1047	
BJS	0	11.58	0.0862	-0.0028	0.1038	0.20
	1	10.18	0.0862	0.0018	0.1031	
	2	10.38	0.0864	0.0014	0.1057	
	3	12.38	0.0869	0.0046	0.1049	
	4	12.38	0.0881	-0.0018	0.1125	
CS	0	5.59	0.1499	-0.0105	0.1490	18.84
	1	4.19	0.1495	-0.0118	0.1404	
	2	5.99	0.1506	-0.0034	0.1495	
	3	4.79	0.1505	-0.0090	0.1436	
	4	4.99	0.1515	-0.0044	0.1532	
SA	0	3.19	0.1706	0.0049	0.1565	23.44
	1	3.59	0.1696	0.0042	0.1530	
	2	2.40	0.1705	0.0070	0.1502	
	3	2.20	0.1697	0.0051	0.1491	
	4	2.20	0.1716	0.0040	0.1519	
dCDH	0	7.98	0.1369	0.0062	0.1536	3.58
	1	7.19	0.1356	0.0067	0.1485	
	2	8.58	0.1372	0.0081	0.1489	
	3	7.98	0.1368	0.0055	0.1452	
	4	7.98	0.1390	0.0071	0.1492	
W	0	7.39	0.1479	0.0049	0.1575	55.06
	1	6.59	0.1467	0.0043	0.1539	
	2	5.99	0.1471	0.0072	0.1519	
	3	5.19	0.1468	0.0052	0.1495	
	4	5.19	0.1490	0.0043	0.1526	

Note: The table reports results from 501 simulations of 40 treated states over 15 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 3: Simulations (CPS wage data, heterogeneous treatment effects): 40 states treated over 10 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	6.19	0.1076	-0.0016	0.1102	0.10
	1	5.19	0.1085	0.0065	0.1077	
	2	4.59	0.1102	0.0008	0.1082	
	3	5.19	0.1110	-0.0069	0.1090	
	4	5.39	0.1102	0.0076	0.1088	
BJS	0	8.38	0.0952	0.0042	0.1079	0.28
	1	10.18	0.0953	-0.0027	0.1124	
	2	7.58	0.0976	0.0027	0.1064	
	3	8.38	0.0989	-0.0010	0.1140	
	4	9.18	0.0978	0.0045	0.1131	
CS	0	4.59	0.1569	-0.0043	0.1528	10.94
	1	4.19	0.1578	0.0056	0.1548	
	2	4.79	0.1571	0.0005	0.1494	
	3	4.39	0.1587	-0.0045	0.1548	
	4	5.59	0.1573	0.0067	0.1554	
SA	0	4.19	0.1719	-0.0066	0.1625	11.27
	1	2.20	0.1715	-0.0001	0.1544	
	2	2.99	0.1726	-0.0044	0.1561	
	3	3.39	0.1738	-0.0102	0.1530	
	4	2.00	0.1724	0.0054	0.1545	
dCDH	0	6.99	0.1441	-0.0063	0.1542	3.50
	1	6.79	0.1459	0.0018	0.1481	
	2	5.39	0.1466	-0.0043	0.1517	
	3	4.99	0.1475	-0.0126	0.1466	
	4	5.79	0.1464	0.0018	0.1500	
W	0	6.99	0.1571	-0.0068	0.1655	28.39
	1	5.19	0.1577	-0.0005	0.1553	
	2	6.19	0.1578	-0.0046	0.1583	
	3	5.79	0.1589	-0.0103	0.1559	
	4	5.79	0.1573	0.0055	0.1577	

Note: The table reports results from 501 simulations of 40 treated states over 10 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 4: Simulations (CPS wage data, heterogeneous treatment effects): 40 states treated over 5 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.39	0.1156	0.0054	0.1146	0.11
	1	6.99	0.1173	-0.0035	0.1255	
	2	6.39	0.1180	0.0062	0.1217	
	3	6.99	0.1185	0.0116	0.1212	
	4	6.59	0.1191	0.0087	0.1246	
BJS	0	7.39	0.1106	0.0023	0.1226	0.26
	1	5.39	0.1116	0.0033	0.1186	
	2	9.18	0.1134	0.0066	0.1246	
	3	6.79	0.1131	0.0031	0.1192	
	4	9.58	0.1145	0.0058	0.1292	
CS	0	5.79	0.1757	0.0005	0.1838	5.19
	1	4.79	0.1765	0.0051	0.1837	
	2	4.39	0.1757	0.0045	0.1717	
	3	6.39	0.1764	-0.0052	0.1896	
	4	7.39	0.1760	-0.0002	0.1902	
SA	0	2.99	0.1828	0.0021	0.1655	2.24
	1	3.79	0.1829	-0.0091	0.1764	
	2	4.19	0.1829	0.0039	0.1734	
	3	5.39	0.1819	0.0080	0.1764	
	4	2.99	0.1840	0.0036	0.1642	
dCDH	0	4.39	0.1591	0.0012	0.1549	3.33
	1	5.79	0.1604	-0.0075	0.1597	
	2	5.59	0.1603	0.0027	0.1627	
	3	5.59	0.1623	0.0080	0.1645	
	4	5.79	0.1630	0.0051	0.1607	
W	0	5.19	0.1792	0.0013	0.1695	10.88
	1	5.59	0.1791	-0.0098	0.1794	
	2	4.59	0.1791	0.0033	0.1765	
	3	6.99	0.1784	0.0074	0.1846	
	4	3.79	0.1801	0.0027	0.1682	

Note: The table reports results from 501 simulations of 40 treated states over 5 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 5: Simulations (CPS wage data, heterogeneous treatment effects): 40 states treated over 2 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	8.38	0.1465	-0.0052	0.1608	0.10
	1	6.39	0.1492	-0.0001	0.1501	
	2	7.19	0.1497	-0.0019	0.1499	
	3	5.99	0.1491	-0.0071	0.1463	
	4	6.39	0.1512	0.0156	0.1562	
BJS	0	5.59	0.1451	0.0083	0.1454	0.22
	1	6.59	0.1450	-0.0063	0.1532	
	2	5.79	0.1478	-0.0121	0.1605	
	3	8.18	0.1472	-0.0083	0.1576	
	4	5.99	0.1509	0.0034	0.1582	
CS	0	7.78	0.2226	0.0033	0.2320	2.61
	1	6.99	0.2226	-0.0059	0.2338	
	2	8.58	0.2239	0.0036	0.2364	
	3	7.58	0.2203	-0.0016	0.2349	
	4	7.19	0.2223	-0.0091	0.2355	
SA	0	8.98	0.2140	-0.0001	0.2354	0.57
	1	5.79	0.2175	0.0013	0.2178	
	2	4.39	0.2173	0.0011	0.2162	
	3	5.79	0.2142	-0.0039	0.2149	
	4	5.19	0.2185	0.0179	0.2238	
dCDH	0	6.59	0.2012	-0.0026	0.2124	2.88
	1	6.19	0.2060	0.0019	0.2081	
	2	4.79	0.2074	0.0000	0.2035	
	3	3.79	0.2078	-0.0047	0.2021	
	4	6.19	0.2096	0.0174	0.2156	
W	0	10.78	0.2238	-0.0012	0.2480	4.33
	1	5.59	0.2293	0.0008	0.2302	
	2	5.99	0.2284	0.0002	0.2273	
	3	5.59	0.2272	-0.0047	0.2245	
	4	6.39	0.2292	0.0165	0.2365	

Note: The table reports results from 501 simulations of 40 treated states over 2 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 6: Simulations (CPS wage data, heterogeneous treatment effects): 30 states treated over 15 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.99	0.1170	-0.0019	0.1157	0.11
	1	4.79	0.1179	-0.0017	0.1148	
	2	5.99	0.1183	0.0017	0.1209	
	3	4.39	0.1193	-0.0036	0.1150	
	4	4.99	0.1182	0.0040	0.1111	
BJS	0	15.57	0.0851	0.0002	0.1138	0.21
	1	16.97	0.0864	-0.0020	0.1189	
	2	17.76	0.0863	0.0050	0.1235	
	3	16.77	0.0872	-0.0040	0.1194	
	4	18.56	0.0872	0.0000	0.1232	
CS	0	5.59	0.1606	0.0043	0.1575	23.31
	1	5.99	0.1602	0.0038	0.1665	
	2	5.79	0.1615	0.0017	0.1596	
	3	6.79	0.1606	0.0064	0.1589	
	4	7.58	0.1600	0.0012	0.1644	
SA	0	2.99	0.1789	-0.0023	0.1576	20.66
	1	2.79	0.1788	-0.0011	0.1516	
	2	2.20	0.1791	0.0009	0.1586	
	3	1.80	0.1814	-0.0039	0.1552	
	4	2.40	0.1793	0.0036	0.1544	
dCDH	0	8.98	0.1437	-0.0010	0.1583	3.63
	1	7.98	0.1435	-0.0006	0.1536	
	2	9.98	0.1433	0.0029	0.1608	
	3	7.39	0.1457	-0.0022	0.1591	
	4	9.58	0.1439	0.0049	0.1542	
W	0	8.58	0.1425	-0.0020	0.1597	54.57
	1	8.98	0.1419	-0.0008	0.1545	
	2	9.18	0.1419	0.0012	0.1609	
	3	6.79	0.1445	-0.0035	0.1580	
	4	9.38	0.1428	0.0039	0.1559	

Note: The table reports results from 501 simulations of 30 treated states over 15 years, with at least one treated state in each of those years. See the note accompanying Table 2 for further information.

Appendix Table 7: Simulations (CPS wage data, homogeneous treatment effects): 40 states treated over 20 years (2 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.99	0.1025	0.0059	0.0997	0.11
	1	5.79	0.1026	0.0064	0.1046	
	2	4.99	0.1038	-0.0075	0.1020	
	3	4.99	0.1039	0.0041	0.1027	
	4	6.39	0.1045	0.0039	0.1047	
BJS	0	12.57	0.0741	-0.0016	0.0967	0.22
	1	16.97	0.0748	-0.0034	0.1034	
	2	16.17	0.0758	-0.0019	0.1073	
	3	12.57	0.0757	-0.0006	0.1000	
	4	15.77	0.0771	-0.0125	0.1045	
BJS (leave out)	0	0.40	0.1401	-0.0016	0.0967	0.59
	1	1.20	0.1402	-0.0034	0.1034	
	2	1.80	0.1419	-0.0019	0.1073	
	3	1.00	0.1407	-0.0006	0.1000	
	4	0.80	0.1428	-0.0125	0.1045	
CS	0	2.99	0.1434	-0.0002	0.1347	42.21
	1	5.59	0.1419	0.0062	0.1378	
	2	4.39	0.1416	0.0006	0.1305	
	3	3.59	0.1429	0.0059	0.1343	
	4	4.79	0.1430	-0.0029	0.1355	
SA	0	0.60	0.1663	0.0018	0.1272	38.92
	1	2.00	0.1664	0.0015	0.1417	
	2	2.00	0.1670	-0.0138	0.1371	
	3	2.00	0.1673	-0.0023	0.1357	
	4	1.80	0.1678	-0.0011	0.1396	
dCDH	0	4.79	0.1375	0.0009	0.1277	5.15
	1	6.59	0.1371	0.0017	0.1422	
	2	4.99	0.1388	-0.0126	0.1370	
	3	5.79	0.1377	-0.0010	0.1373	
	4	5.19	0.1386	-0.0010	0.1400	
W	0	4.59	0.1341	0.0015	0.1284	96.38
	1	6.59	0.1341	0.0011	0.1434	
	2	6.39	0.1357	-0.0141	0.1382	
	3	5.79	0.1344	-0.0027	0.1363	
	4	5.99	0.1355	-0.0015	0.1400	
TWFE	0	2.79	0.1367	0.0005	0.1230	0.16
	1	3.79	0.1365	0.0010	0.1378	
	2	4.39	0.1360	-0.0136	0.1327	
	3	4.99	0.1369	-0.0014	0.1342	
	4	4.59	0.1372	-0.0015	0.1365	
TWFE (no pre)	0	5.39	0.1011	0.0053	0.0969	0.11
	1	5.59	0.1009	0.0059	0.1036	
	2	4.39	0.1020	-0.0087	0.1002	
	3	4.99	0.1022	0.0036	0.1012	
	4	5.19	0.1028	0.0035	0.1042	

Note: The table reports results from 501 simulations of 40 treated states over 20 years, with two treated states in each of those years. Treatment effects are homogeneous and drawn from a normal distribution, with an average value set to 5 percent of the average wage and a standard deviation equal to 10 percent of the average wage. TWFE denotes the two-way fixed effects estimator for a fully dynamic specification, estimating both pre-event and post-event coefficients. TWFE (no pre) denotes a two-way fixed effects specification that estimates only post-event coefficients. See the note accompanying Table 2 for further information.

Appendix Table 8: Simulations (i.i.d. data, homogeneous treatment effects): 40 states treated over 20 years (2 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	5.39	0.1285	0.0005	0.1265	0.12
	1	4.99	0.1295	0.0075	0.1304	
	2	4.59	0.1297	-0.0105	0.1250	
	3	4.59	0.1303	0.0035	0.1264	
	4	4.99	0.1304	0.0013	0.1270	
BJS	0	17.56	0.0936	0.0002	0.1306	0.24
	1	14.77	0.0938	-0.0019	0.1229	
	2	16.37	0.0942	0.0024	0.1334	
	3	14.37	0.0942	-0.0037	0.1263	
	4	15.97	0.0969	0.0020	0.1306	
BJS (leave out)	0	1.60	0.1771	0.0002	0.1306	0.25
	1	0.60	0.1761	-0.0019	0.1229	
	2	1.60	0.1762	0.0024	0.1334	
	3	1.80	0.1754	-0.0037	0.1263	
	4	0.20	0.1796	0.0020	0.1306	
CS	0	3.99	0.1794	-0.0103	0.1709	32.61
	1	4.39	0.1798	-0.0011	0.1770	
	2	4.99	0.1783	0.0017	0.1673	
	3	5.19	0.1788	0.0047	0.1698	
	4	2.99	0.1798	-0.0036	0.1670	
SA	0	2.00	0.2084	-0.0040	0.1681	51.48
	1	2.00	0.2099	0.0015	0.1803	
	2	1.60	0.2096	-0.0169	0.1739	
	3	1.20	0.2087	-0.0032	0.1685	
	4	1.80	0.2089	-0.0033	0.1762	
dCDH	0	5.39	0.1718	-0.0054	0.1678	3.64
	1	6.19	0.1729	0.0022	0.1819	
	2	5.79	0.1730	-0.0163	0.1747	
	3	5.39	0.1722	-0.0024	0.1693	
	4	5.79	0.1726	-0.0045	0.1774	
W	0	5.99	0.1680	-0.0047	0.1693	87.35
	1	7.19	0.1691	0.0009	0.1819	
	2	5.39	0.1694	-0.0175	0.1760	
	3	6.19	0.1683	-0.0039	0.1701	
	4	6.39	0.1691	-0.0041	0.1773	
TWFE	0	4.99	0.1707	-0.0064	0.1622	0.16
	1	4.59	0.1719	0.0008	0.1774	
	2	5.39	0.1705	-0.0178	0.1699	
	3	3.79	0.1708	-0.0028	0.1647	
	4	4.19	0.1709	-0.0048	0.1717	
TWFE (no pre)	0	4.99	0.1267	-0.0004	0.1230	0.11
	1	4.39	0.1273	0.0069	0.1297	
	2	4.39	0.1273	-0.0117	0.1227	
	3	3.59	0.1281	0.0034	0.1239	
	4	5.39	0.1281	0.0013	0.1264	

Note: The table reports results from 501 simulations of 40 treated states over 20 years, with two treated states in each of those years. Treatment effects are homogeneous and drawn from a normal distribution, with an average value set to 5 percent of the average wage and a standard deviation equal to 10 percent of the average wage. See the note accompanying Appendix Table 7 for further information.

Appendix Table 9: Simulations (i.i.d. data, heterogeneous treatment effects): 40 states treated over 30 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	5.39	0.1267	0.0035	0.1285	0.07
	1	6.79	0.1277	-0.0051	0.1317	
	2	5.79	0.1275	-0.0009	0.1267	
	3	4.79	0.1279	-0.0022	0.1298	
	4	6.19	0.1298	0.0103	0.1359	
BJS	0	27.54	0.0679	-0.0025	0.1211	0.21
	1	31.74	0.0694	-0.0016	0.1291	
	2	31.54	0.0692	-0.0052	0.1323	
	3	28.94	0.0703	-0.0012	0.1276	
	4	30.54	0.0702	0.0030	0.1328	
CS	0	3.79	0.1754	0.0006	0.1609	57.13
	1	6.19	0.1756	0.0080	0.1814	
	2	5.39	0.1764	-0.0002	0.1733	
	3	4.19	0.1753	-0.0044	0.1625	
	4	4.39	0.1767	0.0068	0.1747	
SA	0	2.00	0.2069	0.0060	0.1679	141.91
	1	2.00	0.2095	-0.0052	0.1789	
	2	1.80	0.2084	0.0010	0.1686	
	3	2.59	0.2087	-0.0019	0.1708	
	4	1.00	0.2120	0.0118	0.1697	
dCDH	0	20.56	0.1156	0.0043	0.1704	4.69
	1	21.16	0.1174	-0.0042	0.1808	
	2	17.96	0.1174	0.0001	0.1682	
	3	20.16	0.1180	-0.0009	0.1714	
	4	18.36	0.1197	0.0118	0.1708	
W	0	10.98	0.1447	0.0065	0.1685	200.93
	1	13.17	0.1471	-0.0047	0.1791	
	2	10.38	0.1469	0.0015	0.1691	
	3	10.58	0.1486	-0.0014	0.1713	
	4	12.57	0.1504	0.0122	0.1709	

Note: The table reports results from 501 simulations of 40 treated states over 30 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 10: Simulations (i.i.d. data, heterogeneous treatment effects): 40 states treated over 10 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	5.39	0.1350	0.0045	0.1385	0.07
	1	5.39	0.1366	0.0138	0.1344	
	2	4.79	0.1377	0.0026	0.1351	
	3	4.39	0.1371	0.0007	0.1330	
	4	4.99	0.1381	0.0098	0.1348	
BJS	0	8.78	0.1189	0.0088	0.1346	0.20
	1	10.78	0.1203	-0.0061	0.1402	
	2	10.78	0.1212	0.0051	0.1417	
	3	8.18	0.1225	0.0013	0.1379	
	4	8.78	0.1222	-0.0017	0.1382	
CS	0	5.59	0.1968	-0.0087	0.1992	13.50
	1	5.99	0.1984	0.0084	0.2008	
	2	4.99	0.1983	0.0050	0.1969	
	3	5.59	0.1970	-0.0048	0.1982	
	4	6.19	0.1967	0.0046	0.1928	
SA	0	4.59	0.2159	-0.0021	0.2047	8.19
	1	2.20	0.2182	0.0081	0.1892	
	2	2.40	0.2178	-0.0041	0.1963	
	3	2.79	0.2162	-0.0038	0.1861	
	4	2.79	0.2161	0.0066	0.1901	
dCDH	0	7.78	0.1815	-0.0006	0.1916	4.35
	1	5.19	0.1856	0.0090	0.1822	
	2	7.98	0.1850	-0.0019	0.1887	
	3	5.99	0.1844	-0.0046	0.1828	
	4	5.19	0.1855	0.0038	0.1809	
W	0	6.39	0.1972	-0.0026	0.2073	32.78
	1	4.19	0.2003	0.0073	0.1905	
	2	5.79	0.1986	-0.0046	0.1985	
	3	4.99	0.1979	-0.0042	0.1888	
	4	5.59	0.1978	0.0066	0.1930	

Note: The table reports results from 501 simulations of 40 treated states over 10 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 11: Simulations (i.i.d. data, heterogeneous treatment effects): 40 states treated over 5 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	4.19	0.1456	0.0048	0.1454	0.07
	1	6.79	0.1480	-0.0008	0.1540	
	2	5.39	0.1478	0.0080	0.1484	
	3	5.99	0.1481	0.0108	0.1493	
	4	6.59	0.1496	0.0148	0.1554	
BJS	0	6.59	0.1385	-0.0059	0.1456	0.20
	1	5.79	0.1399	-0.0151	0.1462	
	2	8.98	0.1409	-0.0066	0.1541	
	3	6.19	0.1427	-0.0064	0.1530	
	4	6.39	0.1445	0.0112	0.1488	
CS	0	6.19	0.2198	0.0006	0.2247	6.42
	1	6.99	0.2231	0.0030	0.2357	
	2	6.39	0.2206	0.0088	0.2205	
	3	7.58	0.2204	0.0002	0.2326	
	4	7.39	0.2218	0.0024	0.2350	
SA	0	3.39	0.2297	-0.0007	0.2111	2.12
	1	4.39	0.2306	-0.0059	0.2273	
	2	3.39	0.2292	0.0019	0.2073	
	3	3.59	0.2267	0.0069	0.2079	
	4	3.59	0.2308	0.0093	0.2091	
dCDH	0	5.19	0.1997	0.0003	0.1937	3.32
	1	4.99	0.2033	-0.0058	0.2016	
	2	4.39	0.2009	0.0037	0.1927	
	3	4.19	0.2024	0.0068	0.1941	
	4	4.99	0.2041	0.0119	0.2007	
W	0	5.79	0.2243	-0.0005	0.2169	13.57
	1	5.79	0.2257	-0.0061	0.2307	
	2	5.39	0.2239	0.0017	0.2113	
	3	4.19	0.2226	0.0067	0.2155	
	4	4.59	0.2258	0.0093	0.2137	

Note: The table reports results from 501 simulations of 40 treated states over 5 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 12: Simulations (i.i.d. data, heterogeneous treatment effects): 40 states treated over 2 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	6.59	0.1840	-0.0062	0.1928	0.09
	1	6.79	0.1868	-0.0009	0.1938	
	2	5.59	0.1861	0.0035	0.1946	
	3	5.59	0.1855	-0.0024	0.1905	
	4	6.19	0.1898	0.0057	0.1874	
BJS	0	6.59	0.1815	-0.0014	0.1939	0.22
	1	6.79	0.1827	-0.0096	0.1917	
	2	7.39	0.1831	-0.0055	0.1960	
	3	6.39	0.1863	-0.0003	0.1902	
	4	7.39	0.1848	0.0186	0.2016	
CS	0	6.39	0.2778	0.0126	0.2799	2.63
	1	8.18	0.2769	-0.0112	0.2915	
	2	7.98	0.2801	-0.0080	0.2935	
	3	7.19	0.2764	-0.0023	0.2897	
	4	6.79	0.2783	-0.0051	0.2833	
SA	0	6.99	0.2671	0.0031	0.2851	0.56
	1	5.39	0.2735	0.0084	0.2770	
	2	3.99	0.2720	0.0096	0.2738	
	3	6.39	0.2640	0.0116	0.2694	
	4	6.19	0.2715	0.0177	0.2776	
dCDH	0	6.79	0.2532	0.0035	0.2571	2.77
	1	6.79	0.2606	0.0079	0.2669	
	2	7.19	0.2590	0.0130	0.2620	
	3	4.19	0.2583	0.0080	0.2585	
	4	6.19	0.2632	0.0159	0.2620	
W	0	9.38	0.2796	0.0033	0.2996	3.36
	1	7.19	0.2891	0.0088	0.2959	
	2	5.79	0.2861	0.0101	0.2848	
	3	4.99	0.2799	0.0123	0.2816	
	4	5.99	0.2861	0.0173	0.2891	

Note: The table reports results from 501 simulations of 40 treated states over 2 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 13: Simulations (i.i.d. data, heterogeneous treatment effects): 40 states treated over 15 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	5.99	0.1312	0.0029	0.1352	0.08
	1	6.79	0.1304	0.0067	0.1386	
	2	4.19	0.1328	0.0057	0.1331	
	3	6.59	0.1324	-0.0056	0.1328	
	4	5.79	0.1342	0.0015	0.1339	
BJS	0	11.98	0.1061	-0.0006	0.1316	0.21
	1	12.57	0.1075	-0.0020	0.1346	
	2	11.58	0.1076	-0.0048	0.1342	
	3	11.38	0.1079	-0.0060	0.1346	
	4	10.58	0.1100	-0.0007	0.1310	
CS	0	6.19	0.1881	-0.0085	0.1910	21.69
	1	3.19	0.1892	-0.0052	0.1813	
	2	7.78	0.1900	0.0001	0.1907	
	3	4.79	0.1878	-0.0095	0.1799	
	4	5.99	0.1902	-0.0083	0.1896	
SA	0	2.20	0.2140	0.0086	0.1912	25.85
	1	3.39	0.2138	0.0106	0.1959	
	2	2.79	0.2145	0.0130	0.1899	
	3	2.99	0.2120	0.0032	0.1929	
	4	3.19	0.2150	0.0083	0.1923	
dCDH	0	8.18	0.1715	0.0114	0.1846	3.51
	1	7.98	0.1721	0.0149	0.1871	
	2	6.99	0.1725	0.0139	0.1846	
	3	8.78	0.1710	0.0029	0.1894	
	4	7.39	0.1744	0.0104	0.1848	
W	0	6.59	0.1856	0.0096	0.1926	63.27
	1	7.58	0.1858	0.0116	0.1978	
	2	6.39	0.1854	0.0141	0.1906	
	3	6.99	0.1836	0.0041	0.1944	
	4	5.79	0.1870	0.0093	0.1937	

Note: The table reports results from 501 simulations of 40 treated states over 15 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 14: Simulations (i.i.d. data, heterogeneous treatment effects): 30 states treated over 15 years (at least 1 per year)

Method	Period	Rejection rate	S.E.	Bias	RMSE	Speed (secs)
GTTY	0	6.39	0.1461	-0.0064	0.1518	0.07
	1	5.79	0.1488	0.0024	0.1494	
	2	5.59	0.1470	-0.0020	0.1476	
	3	4.59	0.1477	-0.0027	0.1432	
	4	5.19	0.1466	0.0104	0.1391	
BJS	0	14.17	0.1059	0.0055	0.1418	0.18
	1	15.37	0.1082	-0.0007	0.1491	
	2	17.37	0.1069	-0.0048	0.1524	
	3	18.96	0.1072	0.0039	0.1607	
	4	15.37	0.1075	0.0096	0.1471	
CS	0	6.19	0.1999	-0.0005	0.2007	21.96
	1	8.18	0.2019	-0.0015	0.2221	
	2	4.99	0.2012	0.0031	0.2023	
	3	5.79	0.1995	0.0128	0.2046	
	4	7.19	0.1983	-0.0071	0.2115	
SA	0	3.59	0.2232	-0.0005	0.2059	20.59
	1	2.40	0.2262	0.0083	0.1997	
	2	4.59	0.2240	0.0018	0.2039	
	3	2.79	0.2245	0.0026	0.1954	
	4	2.79	0.2234	0.0146	0.1904	
dCDH	0	10.58	0.1810	0.0011	0.2072	3.59
	1	8.98	0.1822	0.0100	0.2019	
	2	9.98	0.1799	0.0057	0.2033	
	3	8.18	0.1811	0.0052	0.1979	
	4	7.58	0.1800	0.0178	0.1925	
W	0	10.58	0.1788	0.0003	0.2083	63.24
	1	9.18	0.1800	0.0091	0.2025	
	2	10.58	0.1779	0.0026	0.2053	
	3	8.58	0.1795	0.0035	0.1977	
	4	8.58	0.1780	0.0153	0.1932	

Note: The table reports results from 501 simulations of 30 treated states over 15 years, with at least one treated state in each of those years. See the note accompanying Table 4 for further information.

Appendix Table 15: Empirical applications: Comparison of t-statistics (always-significant effects)

	$\|t\|$	$\mathbb{1}_{\{\|t\|>4\}}$	$\mathbb{1}_{\{\|t\|>8\}}$
Panel A: Unweighted			
BJS	1.5334	0.3793	0.1379
	(0.2769)	(0.0866)	(0.0457)
CS	-0.1498	-0.0690	0.0000
	(0.1832)	(0.0818)	(0.0000)
SA	0.5620	0.1724	0.0172
	(0.2163)	(0.0894)	(0.0172)
dCDH	1.0068	0.3103	0.0690
	(0.2346)	(0.0885)	(0.0336)
Panel B: Weighted (outcomes)			
BJS	1.6800	0.4359	0.1568
	(0.3428)	(0.1076)	(0.0558)
CS	-0.1863	-0.0207	0.0000
	(0.2274)	(0.0778)	(0.0000)
SA	0.4857	0.1495	0.0101
	(0.2821)	(0.0953)	(0.0103)
dCDH	0.8941	0.2965	0.0384
	(0.2772)	(0.1063)	(0.0199)
Panel C: Weighted (papers)			
BJS	1.7600	0.4461	0.1605
	(0.2837)	(0.0818)	(0.0521)
CS	-0.0756	-0.0282	0.0000
	(0.1837)	(0.0811)	(0.0000)
SA	0.4884	0.1654	0.0147
	(0.2146)	(0.0869)	(0.0147)
dCDH	0.8940	0.2892	0.0588
	(0.2350)	(0.0883)	(0.0290)

Note: This table describes the relationship between each estimator and the absolute t-statistics of the dynamic treatment effect estimates for the subsample of coefficients for which all five methods yield a statistically significant effect. See Table 9 for further information.

Appendix Table 16: Empirical applications: Comparison of t-statistics (all estimates)

	$\lvert t \rvert$		$\mathbb{1}_{\{\lvert t \rvert>1.96\}}$		$\mathbb{1}_{\{\lvert t \rvert>4\}}$		$\mathbb{1}_{\{\lvert t \rvert>8\}}$	
Panel A: Unweighted								
BJS	0.5045	0.4715	0.0835	0.0747	0.0882	0.0843	0.0204	0.0189
	(0.1118)	(0.0914)	(0.0338)	(0.0223)	(0.0203)	(0.0165)	(0.0072)	(0.0096)
CS	-0.2720	-0.2753	-0.0811	-0.0820	-0.0074	-0.0074	0.0025	0.0025
	(0.0846)	(0.0777)	(0.0311)	(0.0213)	(0.0143)	(0.0133)	(0.0025)	(0.0067)
SA	0.7074	0.7041	0.0628	0.0619	0.0965	0.0965	0.0198	0.0198
	(0.2036)	(0.1791)	(0.0333)	(0.0218)	(0.0204)	(0.0162)	(0.0069)	(0.0088)
dCDH	0.5937	0.4312	0.1347	0.0944	0.2351	0.2351	0.1683	0.1683
	(0.1109)	(0.0906)	(0.0355)	(0.0236)	(0.0248)	(0.0207)	(0.0186)	(0.0175)
Panel B: Weighted (outcomes)								
BJS	0.3672	0.2885	0.0710	0.0514	0.0612	0.0529	0.0134	0.0110
	(0.1043)	(0.0957)	(0.0355)	(0.0232)	(0.0183)	(0.0135)	(0.0049)	(0.0072)
CS	-0.2803	-0.2837	-0.0780	-0.0789	-0.0089	-0.0089	0.0028	0.0028
	(0.0876)	(0.0909)	(0.0318)	(0.0231)	(0.0146)	(0.0140)	(0.0028)	(0.0054)
SA	0.7915	0.7882	0.0798	0.0789	0.0982	0.0982	0.0223	0.0223
	(0.2286)	(0.2021)	(0.0353)	(0.0228)	(0.0210)	(0.0156)	(0.0078)	(0.0082)
dCDH	0.4872	0.4079	0.1111	0.0926	0.1663	0.1663	0.1018	0.1018
	(0.1153)	(0.0959)	(0.0370)	(0.0245)	(0.0224)	(0.0168)	(0.0126)	(0.0119)
Panel C: Weighted (papers)								
BJS	0.3034	0.0534	0.0847	0.0478	0.0429	0.0233	0.0093	-0.0006
	(0.1200)	(0.3690)	(0.0520)	(0.0477)	(0.0105)	(0.0213)	(0.0034)	(0.0184)
CS	0.0817	0.0713	0.0189	0.0161	0.0555	0.0555	0.0138	0.0138
	(0.1601)	(0.3473)	(0.0537)	(0.0515)	(0.0338)	(0.0340)	(0.0137)	(0.0152)
SA	2.6647	2.6543	0.1360	0.1332	0.1538	0.1538	0.0974	0.0974
	(0.9733)	(0.9094)	(0.0532)	(0.0496)	(0.0355)	(0.0343)	(0.0341)	(0.0314)
dCDH	0.1893	0.1144	0.0313	0.0206	0.1040	0.1040	0.0792	0.0792
	(0.1188)	(0.3357)	(0.0424)	(0.0403)	(0.0194)	(0.0208)	(0.0165)	(0.0175)
Controls		X		X		X		X

Note: This table describes the relationship between each estimator and the absolute t-statistics of the dynamic treatment effect estimates for the full set of event-study coefficients, including those which only a subset of methods can estimate. The estimates in columns 2, 4, 6, and 8 include paper-outcome-period fixed effects. See Table 9 for further information.

Appendix Table 17: Empirical applications: Comparison of t-statistics (pre-treatment periods)

	$\lvert t \rvert$	$\mathbb{1}_{\{\lvert t \rvert>1.96\}}$	$\mathbb{1}_{\{\lvert t \rvert>4\}}$	$\mathbb{1}_{\{\lvert t \rvert>8\}}$
Panel A: Unweighted				
BJS	0.5183	0.1429	0.1250	0.0089
	(0.1256)	(0.0407)	(0.0339)	(0.0063)
CS	-0.4403	-0.1295	-0.0759	0.0000
	(0.0813)	(0.0300)	(0.0214)	(0.0000)
SA	0.3031	-0.0268	-0.0179	0.0134
	(0.2843)	(0.0355)	(0.0264)	(0.0077)
dCDH	-0.0004	-0.0134	-0.0000	0.0000
	(0.0950)	(0.0361)	(0.0276)	(0.0000)
Panel B: Weighted (outcomes)				
BJS	0.4278	0.1198	0.0972	0.0069
	(0.1131)	(0.0378)	(0.0282)	(0.0049)
CS	-0.3218	-0.0851	-0.0434	0.0000
	(0.0823)	(0.0307)	(0.0219)	(0.0000)
SA	0.6721	-0.0035	0.0035	0.0234
	(0.4774)	(0.0341)	(0.0249)	(0.0134)
dCDH	-0.0188	-0.0130	0.0000	0.0000
	(0.0860)	(0.0318)	(0.0222)	(0.0000)
Panel C: Weighted (papers)				
BJS	0.2539	0.0913	0.0563	0.0030
	(0.1149)	(0.0372)	(0.0185)	(0.0021)
CS	-0.2345	-0.0194	0.0013	0.0000
	(0.1087)	(0.0328)	(0.0208)	(0.0000)
SA	5.3443	0.1852	0.1881	0.1500
	(2.6215)	(0.0803)	(0.0805)	(0.0751)
dCDH	-0.0237	0.0008	0.0000	0.0000
	(0.0967)	(0.0269)	(0.0109)	(0.0000)

Note: This table presents results analogous to those in Appendix Table 16, but for the subsample of event-study coefficients corresponding to pre-treatment periods.