ECON 771 Empirical Exercise: DiD

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Contents

1 Introduction[1]

This report discusses the treatment effect of insurance expansion across states on their amount of hospital uncompensated care.

Here is the Github Repo containing all necessary files to reproduce results in this report.

2 Summary statistics

Provide and discuss a table of simple summary statistics showing the mean, standard deviation, min, and max of hospital total revenues and uncompensated care over time.

Year	Mean	SD	Min	Max
2003	284.45	382.51	1.66	4722.76
2004	318.34	425.26	0.27	5525.73
2005	372.57	504.06	2.74	6398.55
2006	423.94	541.82	1.33	6718.17
2007	469.25	614.23	0.99	8577.05
2008	505.46	637.21	0.97	7743.08
2009	537.56	686.40	0.89	9846.46
2010	557.14	732.24	0.84	10185.42
2011	561.73	799.10	1.65	10572.29
2012	591.13	842.73	1.45	11865.32
2013	624.32	901.07	0.95	12216.59
2014	679.72	1019.82	1.09	13376.35
2015	742.39	1059.18	1.05	14143.53
2016	822.64	1207.48	2.22	14998.23
2017	854.10	1337.37	1.72	16305.91
2018	864.96	1430.90	1.33	18633.71
2019	879.49	1488.18	3.00	18078.51

Table 1: Summary statistics of total hospital revenus

As shown in Table 1, mean total hospital revenues increased dramatically between 2003 and 2009. Similarly, uncompensated care almost doubles during this time. However, as seen in Table 2, there was a significant decline in uncompensated care between 2013 and 2015. This provides some evidence that insurance expansions during this time are associated with decreases in uncompensated care.

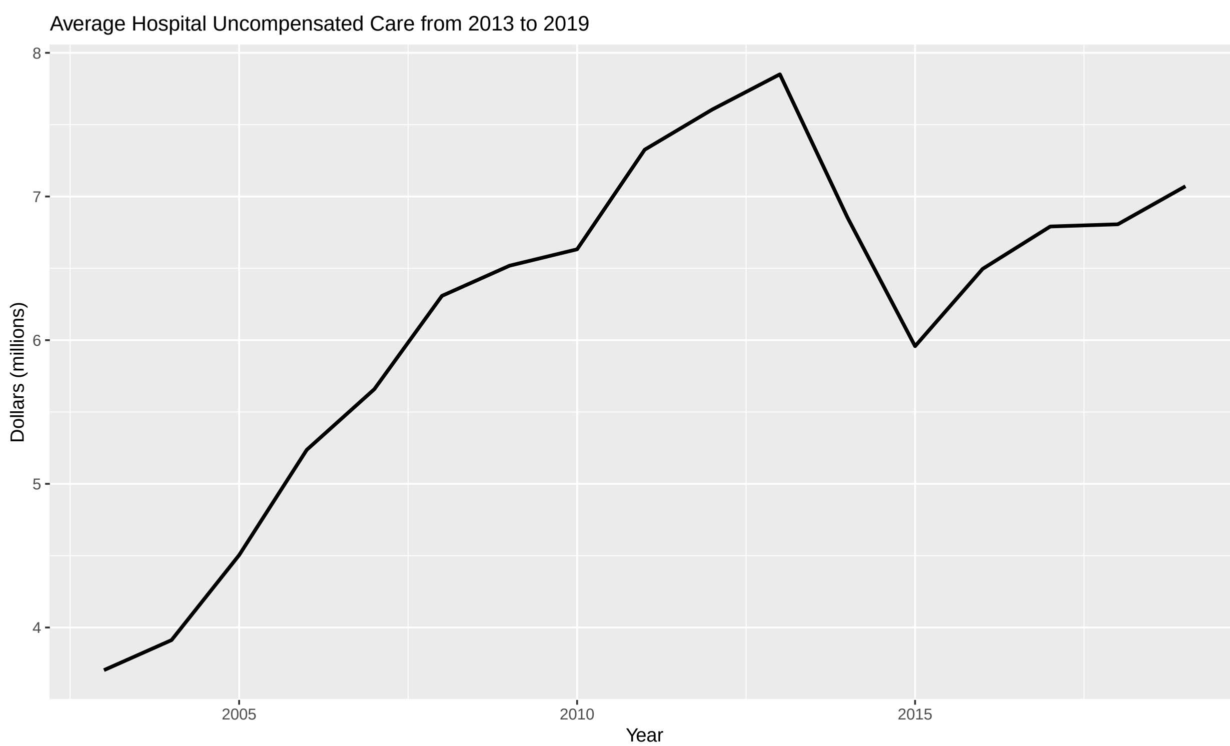
[1]Values in this report are all reported in million dollars, unless otherwise specified

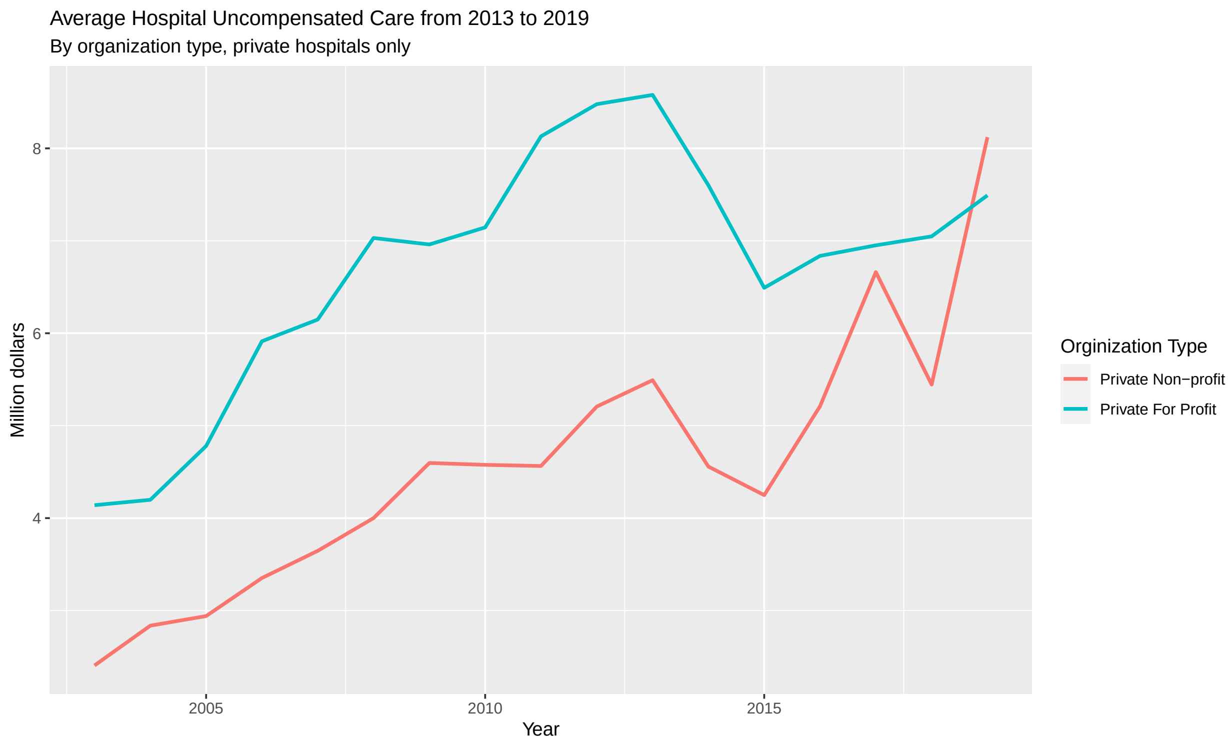
Year	Mean	SD	Min	Max
2003	3.70	5.54	0.00	35.84
2004	3.91	5.41	0.01	35.24
2005	4.50	6.21	0.01	40.32
2006	5.24	6.98	0.01	47.71
2007	5.66	7.36	0.01	48.93
2008	6.31	8.32	0.01	54.97
2009	6.52	7.98	0.02	47.72
2010	6.63	8.21	0.02	49.12
2011	7.33	9.64	0.06	64.37
2012	7.61	9.98	0.09	66.57
2013	7.85	10.07	0.09	61.93
2014	6.85	9.25	0.11	64.84
2015	5.96	8.14	0.09	55.21
2016	6.50	8.88	0.11	56.24
2017	6.79	9.17	0.09	56.76
2018	6.81	9.64	0.10	62.15
2019	7.07	10.26	0.07	59.87

Table 2: Summary statistics of uncompensated care

3 Trend of mean hospital uncompensated care

Create a figure showing the mean hospital uncompensated care from 2003 to 2019. Show this trend separately by hospital ownership type (private not for profit and private for profit).





4 Two-way fixed-effects (TWFE) regression model

Using a simple DD identification strategy, estimate the effect of Medicaid expansion on hospital uncompensated care using a traditional two-way fixed effects (TWFE) estimation:

$$y_{it} = \alpha_i + \gamma_t + \delta D_{it} + \varepsilon_{it}, \tag{1}$$

where $D_{it} = 1(E_i \leq t)$ in Equation (1) is an indicator set to 1 when a hospital is in a state that expanded as of year t or earlier, γ_t denotes time fixed effects, α_i denotes hospital fixed effects, and y_{it} denotes the hospital's amount of uncompensated care in year t. Present four estimates from this estimation in a table: one based on the full sample (regardless of treatment timing); one when limiting to the 2014 treatment group (with never treated as the control group); one when limiting to the 2015 treatment group (with never treated as the control group); and one when limiting to the 2016 treatment group (with never treated as the control group). Briefly explain any differences.

The estimates are similar across all four specifications as shown below. Isolating cohorts with the same treatment timing works as a robustness check for the full TWFE estimate which assumes a single treatment timing.

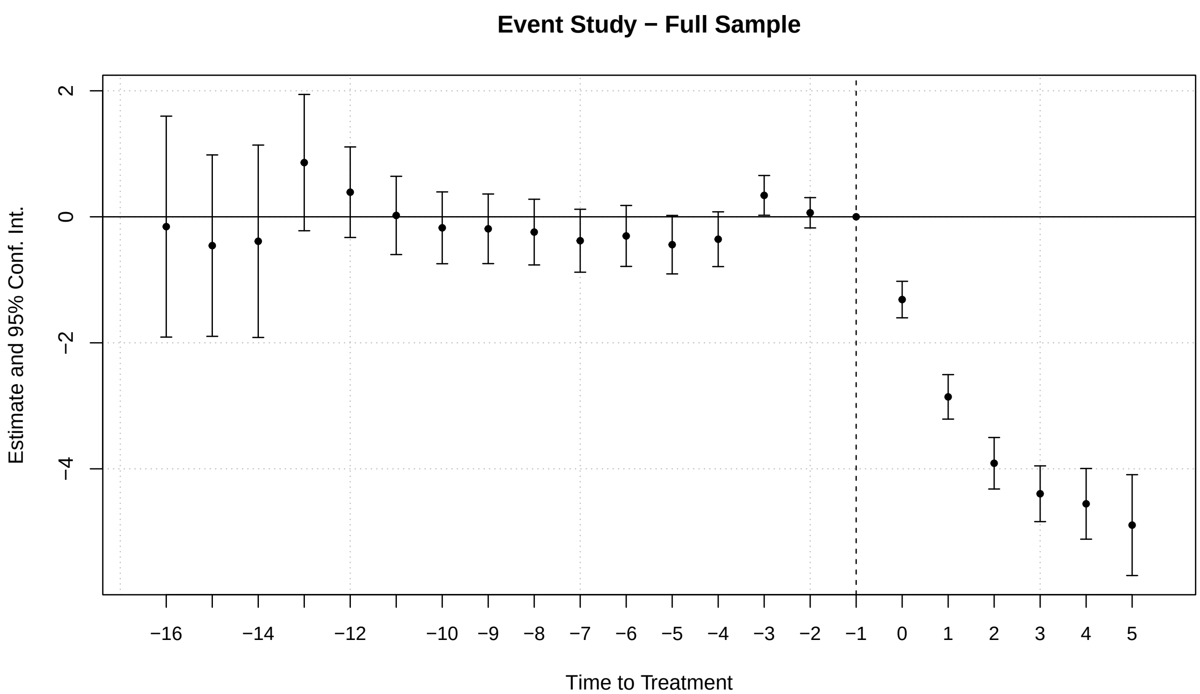
	Full Sample	Expand 2014	Expand 2015	Expand 2016
Expansion	-3.05	-3.31	-2.27	-3.34
	(0.17)	(0.20)	(0.28)	(0.43)

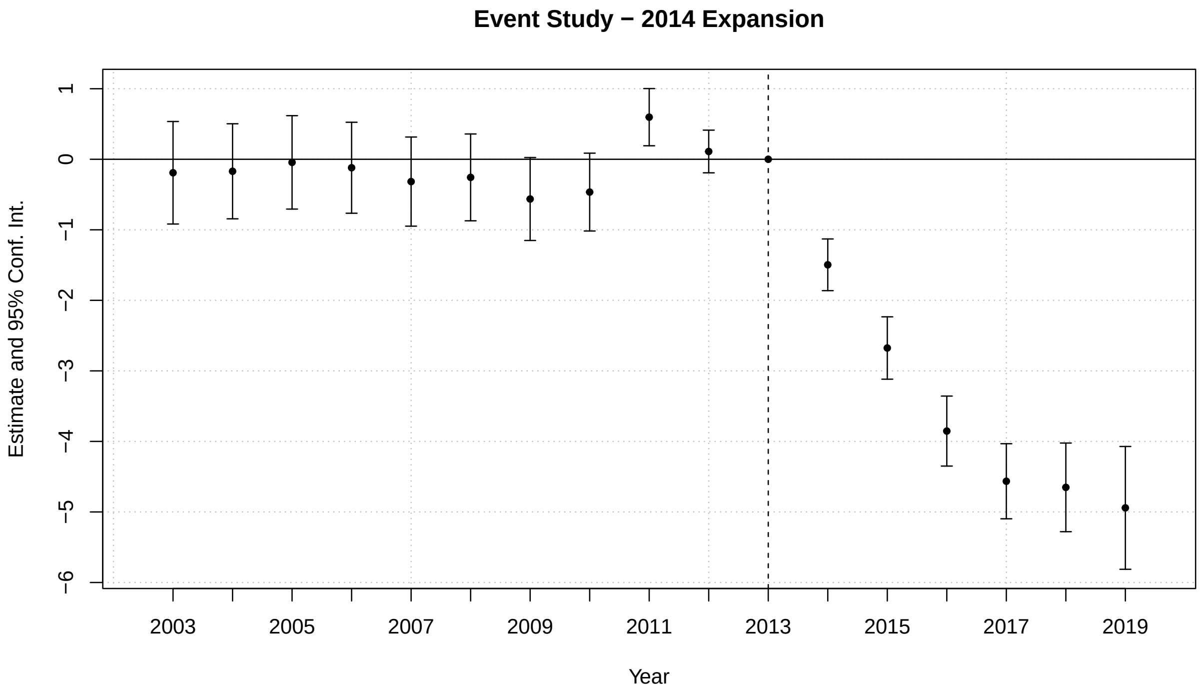
5 Event study

Estimate an "event study" version of the specification in part 3:

$$y_{it} = \alpha_i + \gamma_t + \sum_{\tau<-1} D_{it}^{\tau}\delta_{\tau} + \sum_{\tau>=0} D_{it}^{\tau}\delta_{\tau} + \varepsilon_{it}, \tag{2}$$

where $D_{it}^{\tau} = 1(t - E_i = \tau)$ in Equation (2) is essentially an interaction between the treatment dummy and a relative time dummy. In this notation and context, τ denotes years relative to Medicaid expansion, so that $\tau = -1$ denotes the year before a state expanded Medicaid, $\tau = 0$ denotes the year of expansion, etc. Estimate with two different samples: one based on the full sample and one based only on those that expanded in 2014 (with never treated as the control group).





6 Sun and Abraham (SA) estimator

Sun and Abraham (SA) show that the δ_τ coefficients in Equation (2) can be written as a non-convex average of all other group-time specific average treatment effects. They propose an interaction weighted specification:

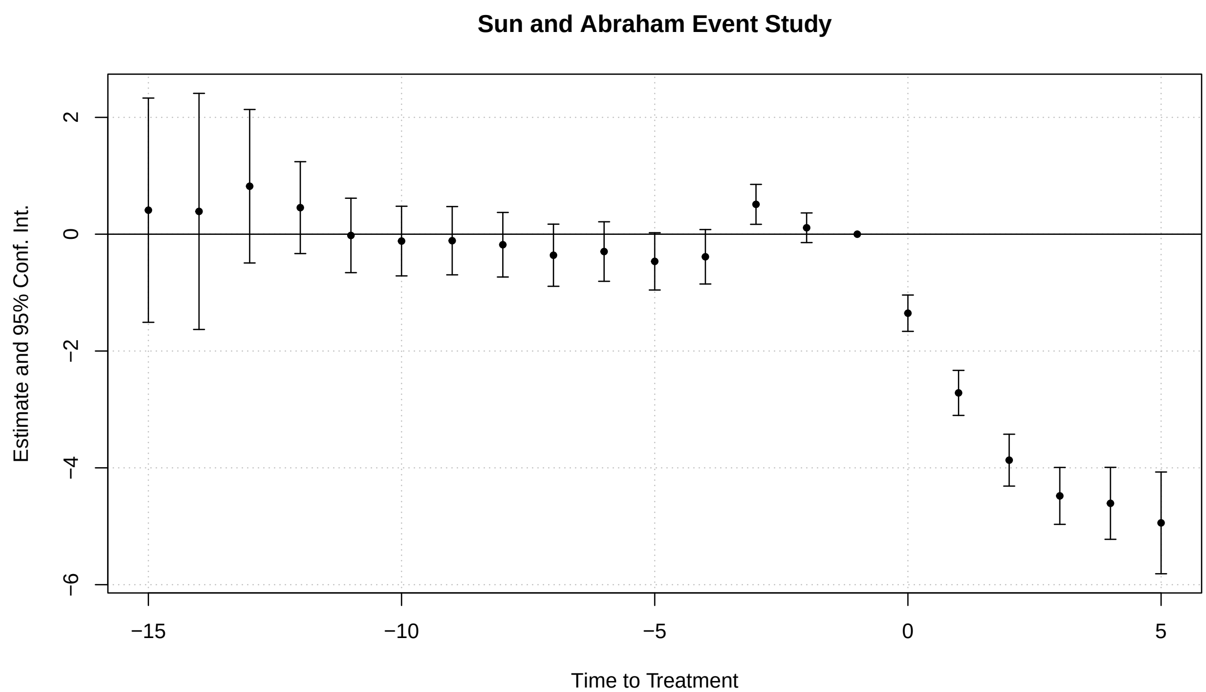
$$y_{it} = \alpha_i + \gamma_t + \sum_{e} \sum_{\tau \neq -1} \left(D_{it}^{\tau} \times 1(E_i = e)\right) \delta_{e,\tau} + \varepsilon_{it}. \tag{3}$$

Re-estimate your event study using the SA specification in Equation (3). Show your results for $\hat{\delta}_{e,\tau}$ in a Table, focusing on states with $E_i = 2014$, $E_i = 2015$, and $E_i = 2016$.

period	cohort	estimate	p_value
-13	2016	0.8726448	0.3265016
-12	2015	0.5937465	0.2207383
-12	2016	-0.2099701	0.7785846
-11	2014	-0.1977816	0.5930024
-11	2015	0.5830957	0.2202449
-11	2016	-0.2846319	0.6930913
-10	2014	-0.1637922	0.6339331
-10	2015	-0.1702857	0.7078823
-10	2016	-0.6201662	0.4343031
-9	2014	-0.0438669	0.8967201
-9	2015	-0.2151776	0.6404181
-9	2016	-0.8827556	0.1935652
-8	2014	-0.1202265	0.7148670
-8	2015	-0.6415921	0.1322876
-8	2016	-1.4463483	0.0245541
-7	2014	-0.3162369	0.3267899
-7	2015	-0.7651736	0.0549251
-7	2016	-1.7260079	0.0223086
-6	2014	-0.2566829	0.4138140
-6	2015	-0.3983957	0.2834543
-6	2016	-1.3502223	0.0236817
-5	2014	-0.5632868	0.0605867
-5	2015	-0.4336379	0.2323092
-5	2016	-0.3887287	0.6023381
-4	2014	-0.4650991	0.0986481
-4	2015	0.0947972	0.8089695
-4	2016	-1.3524235	0.0491026
-3	2014	0.5971007	0.0039181
-3	2015	0.7196843	0.0165733
-3	2016	-1.1956290	0.0264466
-2	2014	0.1105012	0.4741531
-2	2015	0.3297405	0.3111935
-2	2016	-0.3558730	0.3548934
0	2014	-1.4960283	0.0000000
0	2015	-0.2444128	0.5238534
0	2016	-1.2582731	0.0086115
1	2014	-2.6756255	0.0000000
1	2015	-2.0981323	0.0000000
1	2016	-4.8571999	0.0000000
2	2014	-3.8532268	0.0000000
2	2015	-3.3097944	0.0000000
2	2016	-5.9270554	0.0000000
3	2014	-4.5647528	0.0000000
3	2015	-3.5688960	0.0000000
3	2016	-6.0174479	0.0000000
4	2014	-4.6514488	0.0000000
4	2015	-3.2794546	0.0000276
5	2014	-4.9423058	0.0000000

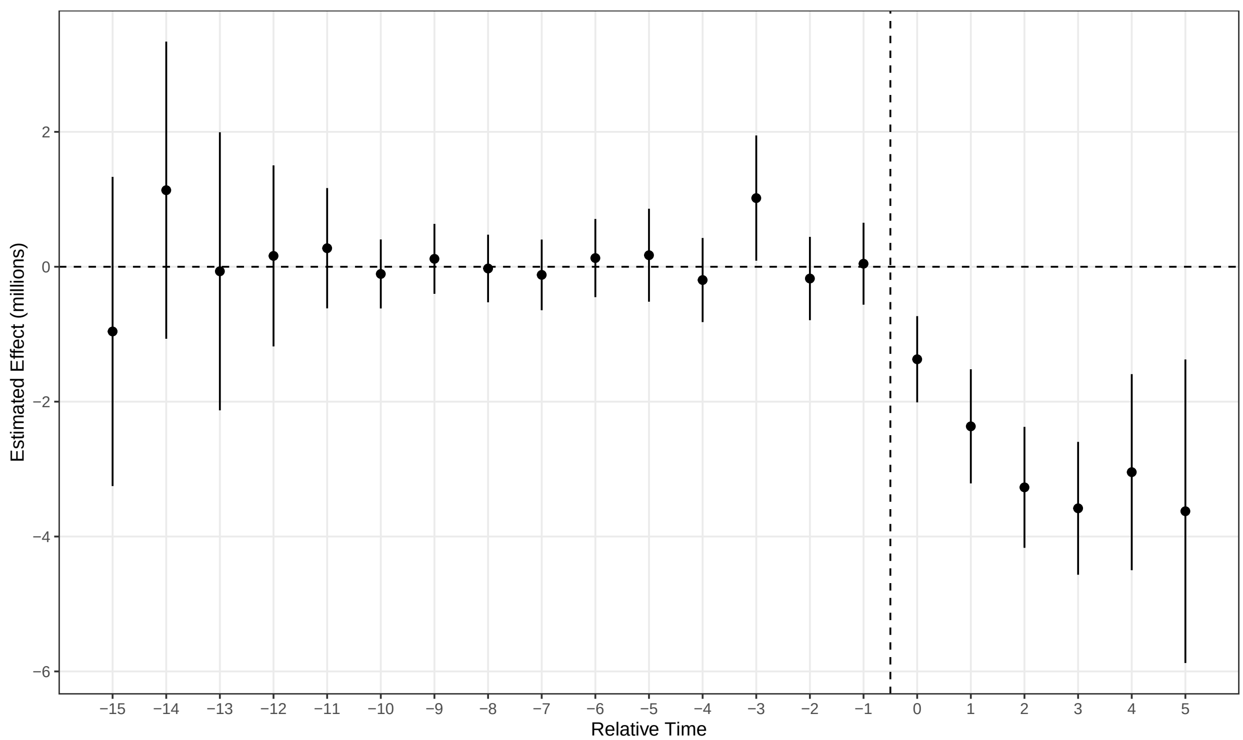
7 Event study graph on the SA estimator

Present an event study graph based on the results in part 5. Hint: you can do this automatically in `R` with the `fixest` package (using the `sunab` syntax for interactions), or with `eventstudyinteract` in `Stata`. These packages help to avoid mistakes compared to doing the tables/figures manually and also help to get the standard errors correct.



8 Callaway and Sant'Anna (CS) estimator

Callaway and Sant'Anna (CS) offer a non-parametric solution that effectively calculates a set of group-time specific differences, $ATT(g,t) = E[y_{it}(g) - y_{it}(\infty)|G_i = g]$, where g reflects treatment timing and t denotes time. They show that under the standard DD assumptions of parallel trends and no anticipation, $ATT(g,t) = E[y_{it} - y_{i,g-1}|G_i = g] - E[y_{it} - y_{i,g-1}|G_i = \infty]$, so that $\hat{ATT}(g,t)$ is directly estimable from sample analogs. CS also propose aggregations of $\hat{ATT}(g,t)$ to form an overall ATT or a time-specific ATT (e.g., ATTs for τ periods before/after treatment). With this framework in mind, provide an alternative event study using the CS estimator. Hint: check out the `did` package in `R` or the `csdid` package in `Stata`.

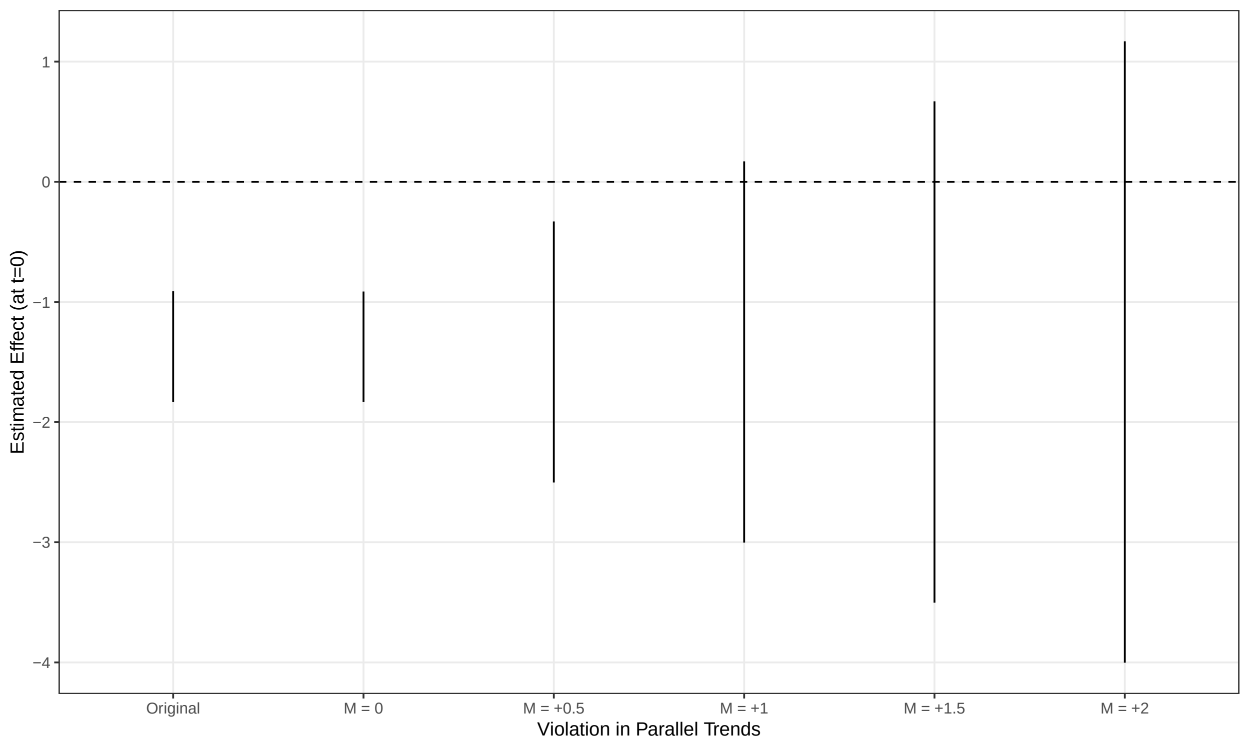


9 Rambachan and Roth (RR) sentivity plot for the CS estimator

Rambachan and Roth (RR) show that traditional tests of parallel pre-trends may be underpowered, and they provide an alternative estimator that essentially bounds the treatment effects by the size of an assumed violation in parallel trends. One such bound RR propose is to limit the post-treatment violation of parallel trends to be no worse than some multiple of the pre-treatment violation of parallel trends. Assuming linear trends, such a relative violation is reflected by

$$\Delta(\bar{M}) = \left\{ \delta : \forall t \geq 0, |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq \bar{M} \times \max_{s<0} |(\delta_{s+1} - \delta_s) - (\delta_s - \delta_{s-1})| \right\}.$$

The authors also propose a similar approach with what they call "smoothness restrictions," in which violations in trends changes no more than M between periods. The only difference is that one restriction is imposed relative to observed trends, and one restriction is imposed using specific values. Using the `HonestDiD` package in `R` or `Stata`, present a sensitivity plot of your CS ATT estimates using smoothness restrictions, with assumed violations of size $M \in \{500, 1000, 1500, 2000\}$. Check out the GitHub repo here for some help in combining the `HonestDiD` package with CS estimates. Note that you'll need to edit the function in that repo in order to use pre-specified smoothness restrictions. You can do that by simply adding `Mvec=Mvec` in the `createSensitivityResults` function for `type=smoothness`.



[2]

[2]Since uncompensated care is in millions in this exercise, M has been scaled appropriately.

10 Discussions and findings

Discuss your findings and compare estimates from different estimators (e.g., are your results sensitive to different specifications or estimators? Are your results sensitive to violation of parallel trends assumptions?).

My results are similar across different specifications and estimators. The estimators for group-time specific treatment effects are slightly smaller than standard DiD estimates, but they have the same sign and general trends. Overall, I find that Medicaid expansion led to a decrease in average hospital uncompensated care of around \$3 million (on a base of around \$7 million). The event studies show that these effects are not fully realized until around the fifth period following expansion. Finally, the RR sensitivity plot shows that these results do not become sensitive to parallel trends until pre-treatment violation equals or exceeds \$1 million.

11 Reflection

Reflect on this assignment. What did you find most challenging? What did you find most surprising?

I think the hardest part of almost any coding exercise is debugging. It can be really frustrating to work on the same error message for hours. Additionally, something I found challenging was having nothing to check my results against. Since most of the similar exercises I've done in the past were replication projects, it was a bit of a different experience having to decide if my results made sense versus blinding checking against some reference results. Since both of these challenges will continue to persist in my own research, the more practice I have in dealing with them, the better.