Final Report for Empirical Exercise 1

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Contents

1 Introduction

Focus on the years from 2003 through 2019, which are years for which data on uncompensated care are available. In your GitHub repository, please be sure to clearly address/answer the following questions.

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.

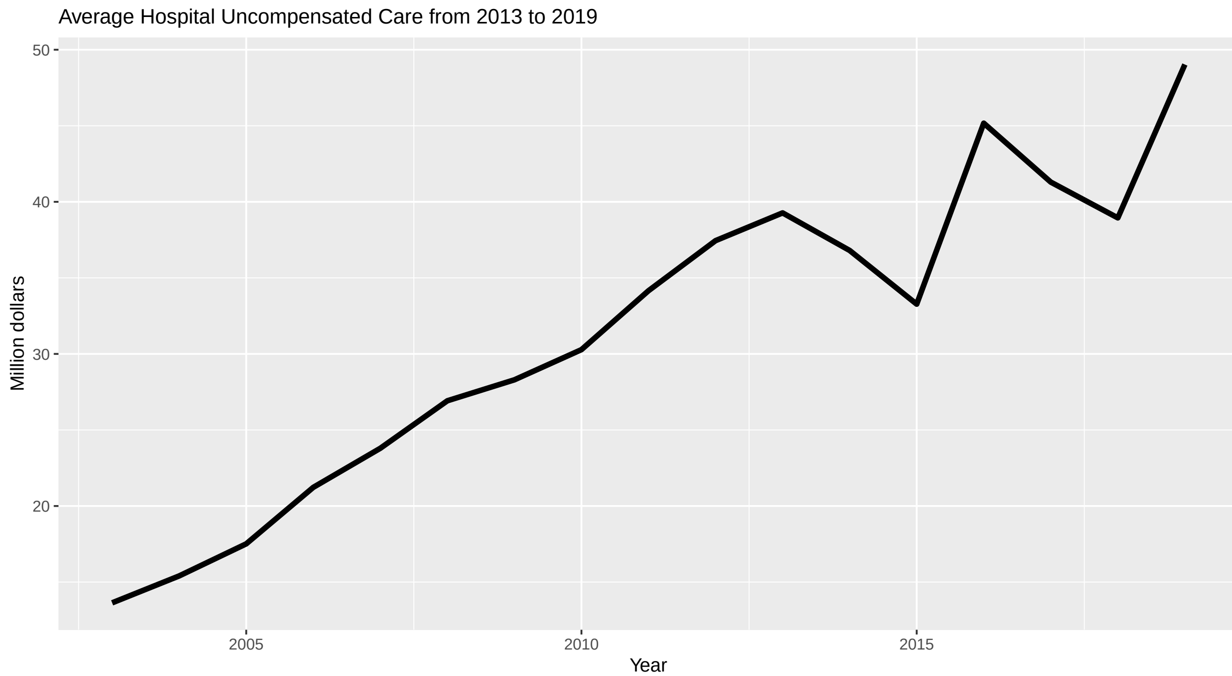
Table 1: Summary Statistics (in Million Dollars)

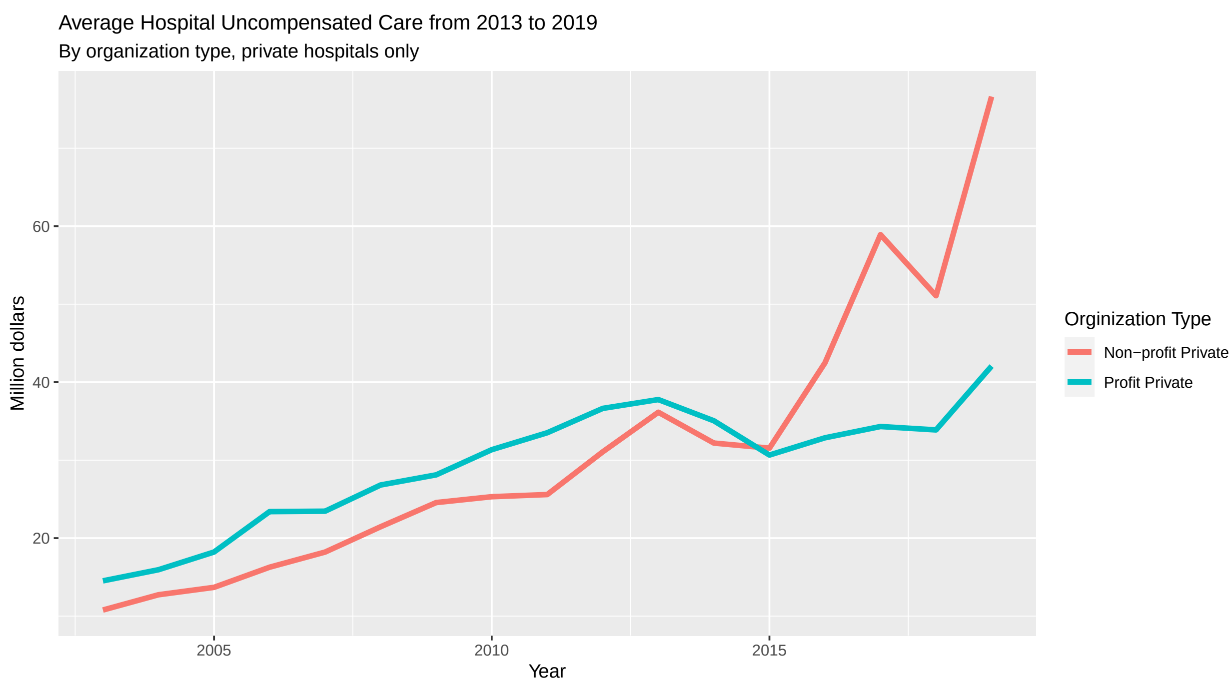
Statistic	N	Mean	St. Dev.	Min	Max
uncomp_care	42,485	30.8	124.2	−97.8	20,404.4
tot_pat_rev	42,485	616.4	1,003.1	−27.6	22,000.9

Discussions:

3 Trend of mean hospital uncompensated

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 TWFE DD Estimation

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.

	Full	2014	2015	2016
Treatment	−31.624***	−34.508***	−32.975***	−35.718***
	(2.755)	(3.110)	(4.360)	(3.728)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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).

	Full	2014
relative_t_expand = -16 × expanded_ever	19.911+	19.911+
	(11.015)	(11.015)
relative_t_expand = -15 × expanded_ever	17.374+	17.374+
	(9.184)	(9.184)
relative_t_expand = -14 × expanded_ever	17.199+	17.199+
	(9.320)	(9.320)
relative_t_expand = -13 × expanded_ever	22.513*	22.513*
	(9.039)	(9.039)
relative_t_expand = -12 × expanded_ever	19.441*	19.441*
	(8.386)	(8.386)
relative_t_expand = -11 × expanded_ever	14.110+	14.110+
	(7.095)	(7.095)
relative_t_expand = -10 × expanded_ever	12.732*	12.732*
	(6.276)	(6.276)
relative_t_expand = -9 × expanded_ever	11.999+	11.999+
	(6.175)	(6.175)
relative_t_expand = -8 × expanded_ever	12.969*	12.969*
	(5.955)	(5.955)
relative_t_expand = -7 × expanded_ever	10.835+	10.835+
	(5.470)	(5.470)
relative_t_expand = -6 × expanded_ever	9.559*	9.559*
	(4.713)	(4.713)
relative_t_expand = -5 × expanded_ever	9.163+	9.163+
	(4.574)	(4.574)
relative_t_expand = -4 × expanded_ever	5.029	5.029
	(4.117)	(4.117)
relative_t_expand = -3 × expanded_ever	4.076	4.076
	(2.713)	(2.713)
relative_t_expand = -2 × expanded_ever	1.179	1.179
	(1.436)	(1.436)
relative_t_expand = 0 × expanded_ever	−14.074***	−14.074***
	(3.989)	(3.989)
relative_t_expand = 1 × expanded_ever	−1.890	−1.890
	(15.903)	(15.903)
relative_t_expand = 2 × expanded_ever	−40.747**	−40.747**
	(11.911)	(11.911)
relative_t_expand = 3 × expanded_ever	−38.559***	−38.559***
	(7.333)	(7.333)
relative_t_expand = 4 × expanded_ever	−42.731***	−42.731***
	(8.600)	(8.600)
relative_t_expand = 5 × expanded_ever	−42.454***	−42.454***
	(11.077)	(11.077)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 SA

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:

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

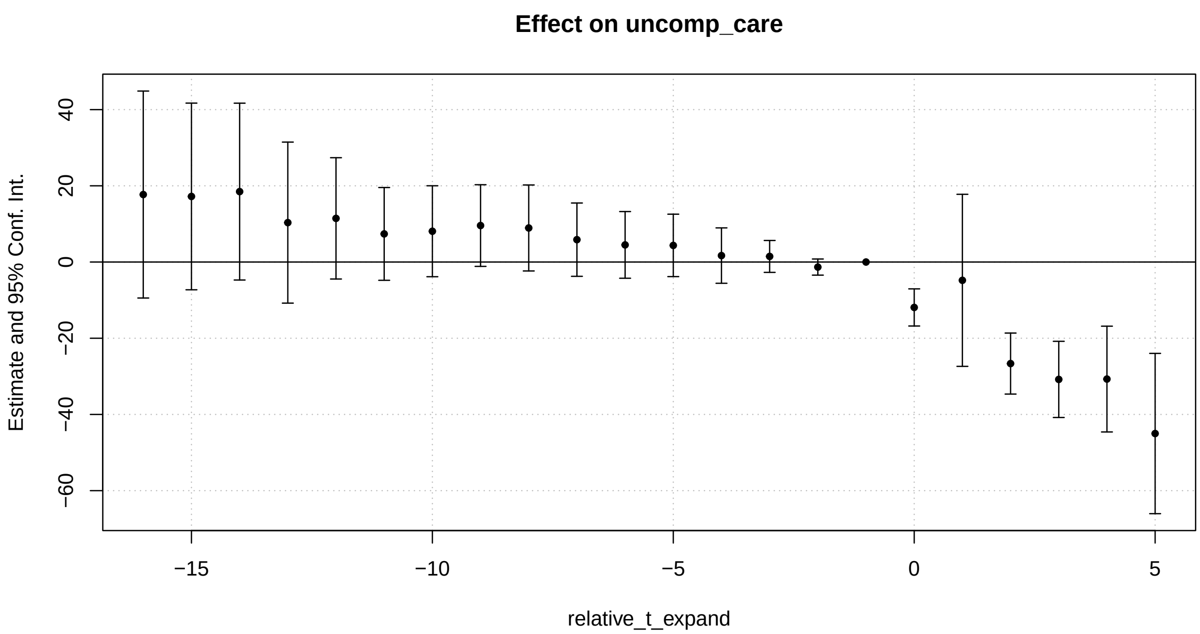
Re-estimate your event study using the SA specification in Equation (3). Show your results for $\hat{\delta}_{e,\tau}$ in a Table, focusing on states with $E_i = 2014$, $E_i = 2015$, and $E_i = 2016$.

	SA_141516
relative_t_expand = -16	17.711
	(13.856)
relative_t_expand = -15	17.212
	(12.498)
relative_t_expand = -14	18.483
	(11.840)
relative_t_expand = -13	10.342
	(10.780)
relative_t_expand = -12	11.457
	(8.120)
relative_t_expand = -11	7.381
	(6.212)
relative_t_expand = -10	8.077
	(6.089)
relative_t_expand = -9	9.572+
	(5.465)
relative_t_expand = -8	8.936
	(5.756)
relative_t_expand = -7	5.868
	(4.907)
relative_t_expand = -6	4.496
	(4.465)
relative_t_expand = -5	4.362
	(4.180)
relative_t_expand = -4	1.689
	(3.708)
relative_t_expand = -3	1.473
	(2.136)
relative_t_expand = -2	−1.326
	(1.079)
relative_t_expand = 0	−11.918***
	(2.486)
relative_t_expand = 1	−4.801
	(11.519)
relative_t_expand = 2	−26.648***
	(4.085)
relative_t_expand = 3	−30.805***
	(5.101)
relative_t_expand = 4	−30.715***
	(7.081)
relative_t_expand = 5	−45.007***
	(10.732)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Event study graph

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 CS

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`.

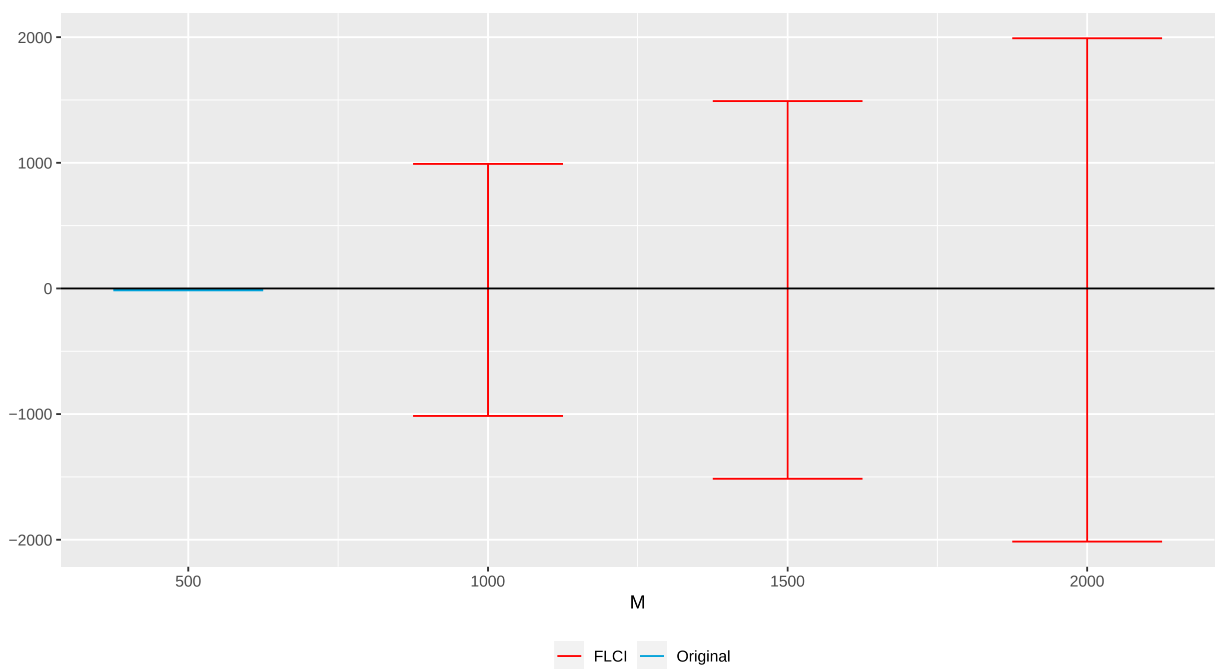
```
##
## Call:
## aggte(MP = CS, type = "dynamic")
##
## Reference: Callaway, Brantly and Pedro H.C. Sant'Anna.  "Difference-in-Differences with Multiple Tim
##
##
## Overall summary of ATT's based on event-study/dynamic aggregation:
##      ATT    Std. Error     [ 95%  Conf. Int.]
##  -25.234        3.4333   -31.9632    -18.5049 *
##
##
## Dynamic Effects:
##  Event time Estimate Std. Error [95% Simult.  Conf. Band]
##         -15   0.3000     1.6911       -4.2686      4.8687
##         -14   1.0300     1.8134       -3.8690      5.9290
##         -13  -0.6035     2.5330       -7.4465      6.2395
##         -12   4.5867     6.8168      -13.8292     23.0026
##         -11  -2.3537     3.1414      -10.8403      6.1329
##         -10  -0.2616     1.3443       -3.8931      3.3700
##          -9  -0.6495     0.9960       -3.3403      2.0413
##          -8   0.7009     1.0684       -2.1854      3.5871
##          -7  -2.9743     1.2210       -6.2728      0.3242
##          -6  -0.9905     1.1201       -4.0164      2.0354
##          -5  -0.5419     2.4455       -7.1485      6.0647
##          -4  -2.2054     2.2316       -8.2342      3.8233
##          -3   2.3350     2.5279       -4.4942      9.1642
##          -2  -2.1738     1.5062       -6.2427      1.8952
##          -1   0.1839     1.5324       -3.9558      4.3236
##           0 -11.9083     1.7832      -16.7258     -7.0908 *
##           1  -4.5353    19.9516      -58.4356     49.3649
##           2 -25.5632     2.2155      -31.5485    -19.5779 *
##           3 -30.9534     2.6261      -38.0479    -23.8589 *
##           4 -31.5138     4.3940      -43.3845    -19.6431 *
##           5 -46.9301     5.5166      -61.8335    -32.0266 *
## ---
## Signif. codes: `*' confidence band does not cover 0
##
## Control Group:  Never Treated,  Anticipation Periods:  0
## Estimation Method:  Doubly Robust
```

9 RR

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`.



10 Discussion 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?).

11 Reflection

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