Final Report for Empirical Exercise 1

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1 Introduction[1]

This report discusses the treatment effect of insurance expansion across states on their amount of hospital uncompensated care. We focus on the years from 2003 through 2019, which are years for which data on uncompensated care are available. 3 different datasets are incorporated to implement the study, which are:

1. **Hospital Cost Report Information System** from CMS - Github Repo
2. **Provider of Services files** from NBER and CMS - Github Repo
3. **Medicaid Expansion** from US Census Data - Github Repo

Organization and access to the data are based on practices provided by Prof. Ian McCarthy.

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

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

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	13.63	32.22	-0.13	777.99
2004	15.40	36.72	0.00	820.25
2005	17.51	37.87	0.00	939.13
2006	21.23	47.75	-2.67	1074.62
2007	23.80	51.80	0.00	1203.37
2008	26.92	57.29	0.00	1361.81
2009	28.30	48.25	0.00	583.98
2010	30.28	72.12	0.00	2793.92
2011	34.16	75.09	-54.94	2057.88
2012	37.45	86.43	-1.24	1881.08
2013	39.27	80.75	-0.34	1812.49
2014	36.80	88.62	-26.45	1989.89
2015	33.27	86.59	-0.53	2037.43
2016	45.17	402.17	-0.04	20404.45
2017	41.30	103.02	-0.03	2746.88
2018	38.94	99.86	0.01	2596.87
2019	49.03	120.98	-97.79	2639.15

Table 1: Summary statistics of uncompensated care

year	Mean	SD	Min	Max
2003	295.00	399.15	1.66	4722.76
2004	330.20	446.63	0.27	5525.73
2005	382.53	518.01	2.40	6398.55
2006	434.84	558.67	1.33	6718.17
2007	488.06	647.81	0.99	8577.05
2008	523.30	666.97	0.97	7743.08
2009	567.38	750.56	0.89	9846.46
2010	585.31	801.05	0.84	10185.42
2011	589.04	865.52	-27.58	10572.29
2012	626.56	942.14	1.45	11865.32
2013	664.35	1014.28	0.95	12751.71
2014	720.92	1111.13	1.09	13376.35
2015	782.63	1157.94	1.05	14143.53
2016	869.10	1314.83	2.22	15618.75
2017	905.54	1442.44	1.72	16305.91
2018	891.57	1566.21	1.33	18633.71
2019	1043.65	1721.83	3.00	22000.93

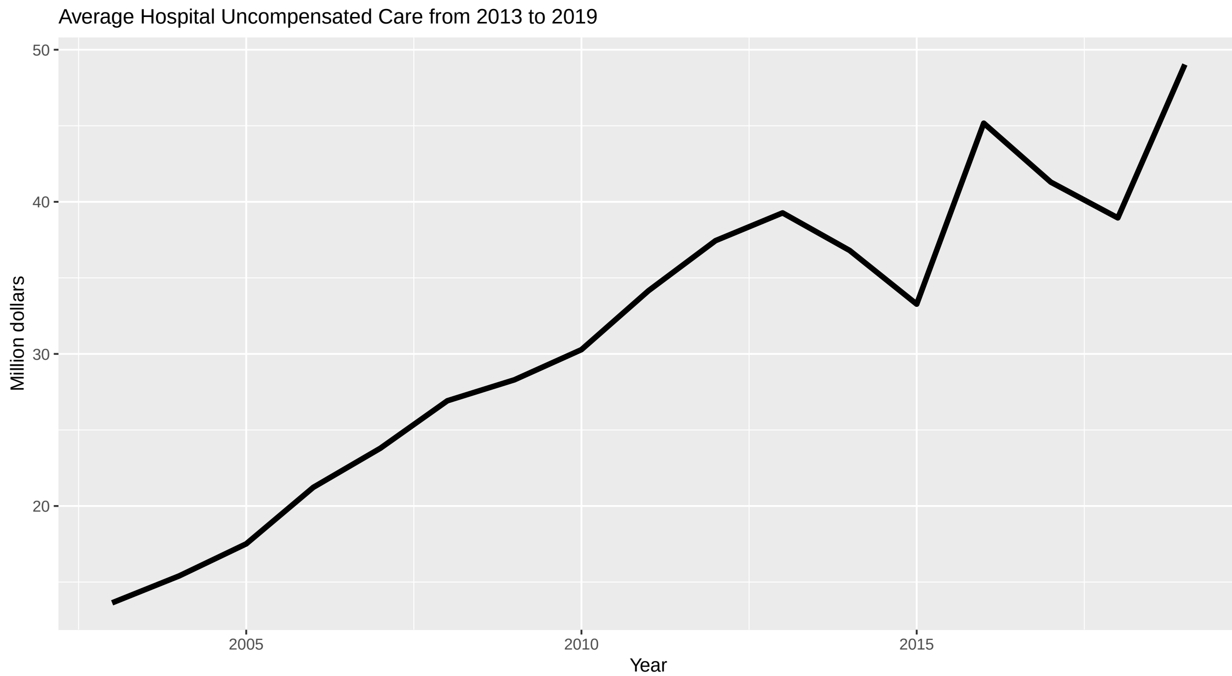
Table 2: Summary statistics of total hospital revenus

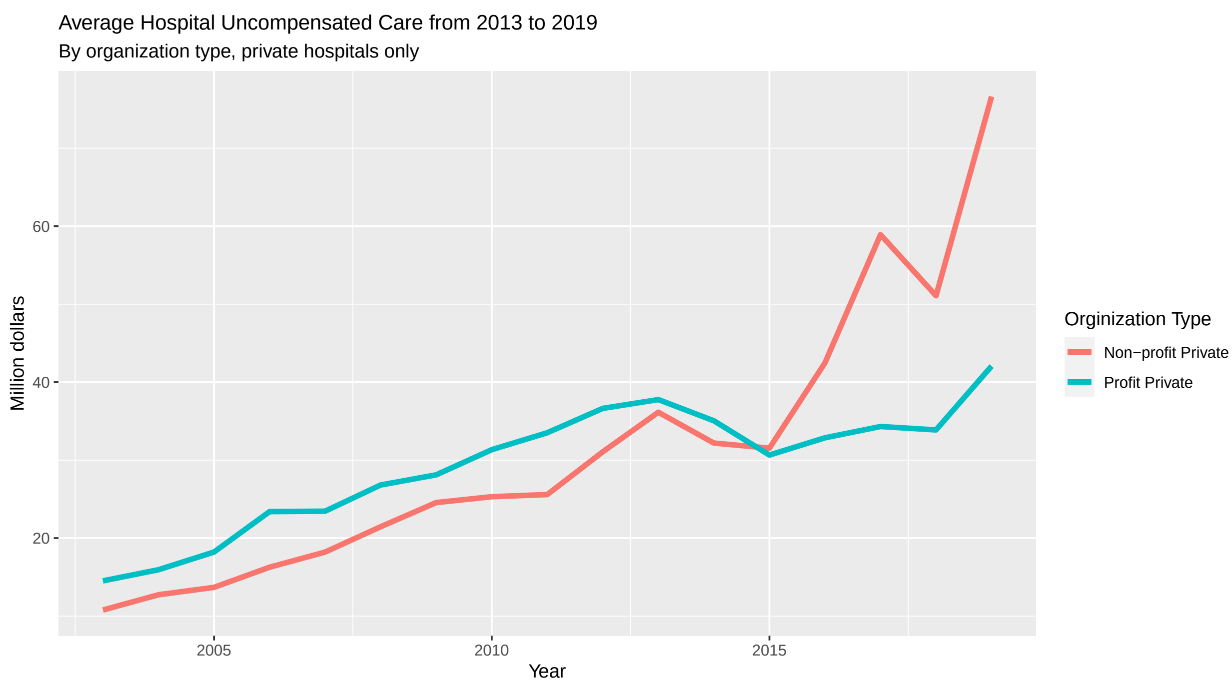
Discussions:

As showed in table, we can see that both the mean and the standard deviation of the two series have increased over time. Also, the rate of increase is similar, both of them have a 5 to 6 times expansion. Therefore, it is reasonable to believe their is a positive correlation between the 2 variables. It gives us an idea that if it is possible that revenue is a decision factor for hospitals to decides its provision of uncompensated care, the expansion of insurance might help the originally uninsured to seek medical support.

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.

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

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

Discussions:

From the table we can see that the estimated treatment effect is similar across all the settings. Recall that one of the hazard of using TWFE is that it assumed common treatment timing. By comparing across groups, we perform a robustness check to strengthen the evidence for the negative effect to exist.

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	
	(11.015)	
relative_t_expand = -15 × expanded_ever	17.374	
	(9.184)	
relative_t_expand = -14 × expanded_ever	17.199	
	(9.320)	
relative_t_expand = -13 × expanded_ever	22.513	
	(9.039)	
relative_t_expand = -12 × expanded_ever	19.441	
	(8.386)	
relative_t_expand = -11 × expanded_ever	14.110	11.285
	(7.095)	(7.375)
relative_t_expand = -10 × expanded_ever	12.732	11.520
	(6.276)	(5.986)
relative_t_expand = -9 × expanded_ever	11.999	11.831
	(6.175)	(6.019)
relative_t_expand = -8 × expanded_ever	12.969	13.905
	(5.955)	(5.946)
relative_t_expand = -7 × expanded_ever	10.835	12.265
	(5.470)	(5.617)
relative_t_expand = -6 × expanded_ever	9.559	9.975
	(4.713)	(4.663)
relative_t_expand = -5 × expanded_ever	9.163	6.750
	(4.574)	(4.368)
relative_t_expand = -4 × expanded_ever	5.029	5.827
	(4.117)	(4.163)
relative_t_expand = -3 × expanded_ever	4.076	6.104
	(2.713)	(2.711)
relative_t_expand = -2 × expanded_ever	1.179	1.069
	(1.436)	(1.683)
relative_t_expand = 0 × expanded_ever	−14.074	−11.436
	(3.989)	(2.689)
relative_t_expand = 1 × expanded_ever	−1.890	−17.508
	(15.903)	(3.484)
relative_t_expand = 2 × expanded_ever	−40.747	−28.414
	(11.911)	(5.208)
relative_t_expand = 3 × expanded_ever	−38.559	−35.401
	(7.333)	(7.076)
relative_t_expand = 4 × expanded_ever	−42.731	−37.893
	(8.600)	(7.415)
relative_t_expand = 5 × expanded_ever	−42.454	−48.649
	(11.077)	(10.334)

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 $E_i = 2016$.

	SA_141516
relative_t_expand = -16 × cohort = 2019	17.711
	(13.856)
relative_t_expand = -15 × cohort = 2019	17.212
	(12.498)
relative_t_expand = -14 × cohort = 2019	18.483
	(11.840)
relative_t_expand = -13 × cohort = 2016	6.027
	(14.461)
relative_t_expand = -13 × cohort = 2019	15.890
	(11.956)
relative_t_expand = -12 × cohort = 2015	9.611
	(7.438)
relative_t_expand = -12 × cohort = 2016	5.758
	(13.055)
relative_t_expand = -12 × cohort = 2019	26.100
	(22.385)
relative_t_expand = -11 × cohort = 2014	6.481
	(6.569)
relative_t_expand = -11 × cohort = 2015	10.229
	(7.737)
relative_t_expand = -11 × cohort = 2016	7.230
	(13.239)
relative_t_expand = -11 × cohort = 2019	15.797
	(9.603)
relative_t_expand = -10 × cohort = 2014	7.460
	(6.439)
relative_t_expand = -10 × cohort = 2015	11.093
	(7.079)
relative_t_expand = -10 × cohort = 2016	3.426
	(14.253)
relative_t_expand = -10 × cohort = 2019	15.855+
	(9.380)
relative_t_expand = -9 × cohort = 2014	9.937+
	(5.591)
relative_t_expand = -9 × cohort = 2015	9.843
	(6.617)
relative_t_expand = -9 × cohort = 2016	2.308
	(14.372)
relative_t_expand = -9 × cohort = 2019	8.764
	(10.088)
relative_t_expand = -8 × cohort = 2014	9.977
	(6.344)
relative_t_expand = -8 × cohort = 2015	6.566
	(6.775)
relative_t_expand = -8 × cohort = 2016	−1.824
	(14.127)
relative_t_expand = -8 × cohort = 2019	7.791
	(7.910)
relative_t_expand = -7 × cohort = 2014	6.834
	(5.423)
relative_t_expand = -7 × cohort = 2015	4.938
	(5.898)
relative_t_expand = -7 × cohort = 2016	−5.734
	(14.208)
relative_t_expand = -7 × cohort = 2019	4.728
	(7.013)
relative_t_expand = -6 × cohort = 2014	5.143
	(4.999)
relative_t_expand = -6 × cohort = 2015	5.508

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 $A\hat{T}T(g,t)$ is directly estimable from sample analogs. CS also propose aggregations of $A\hat{T}T(g,t)$ 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`.

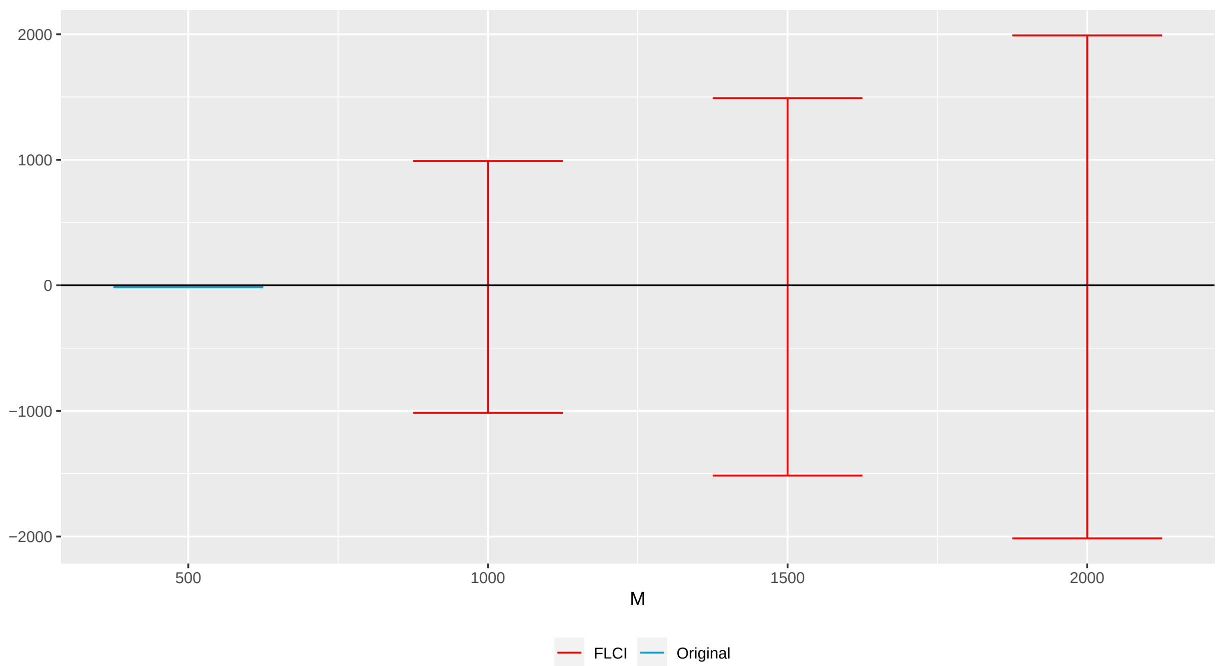
	CS_event
ATT(-15)	0.300
	(1.732)
ATT(-14)	1.030
	(1.711)
ATT(-13)	−0.603
	(2.510)
ATT(-12)	4.587
	(6.677)
ATT(-11)	−2.354
	(3.353)
ATT(-10)	−0.262
	(1.368)
ATT(-9)	−0.650
	(0.972)
ATT(-8)	0.701
	(1.114)
ATT(-7)	−2.974
	(1.304)
ATT(-6)	−0.991
	(1.067)
ATT(-5)	−0.542
	(2.485)
ATT(-4)	−2.205
	(2.228)
ATT(-3)	2.335
	(2.350)
ATT(-2)	−2.174
	(1.500)
ATT(-1)	0.184
	(1.606)
ATT(0)	−11.908
	(1.687)
ATT(1)	−4.535
	(20.046)
ATT(2)	−25.563
	(1.997)
ATT(3)	−30.953
	(2.779)
ATT(4)	−31.514
	(4.069)
ATT(5)	−46.930
	(5.835)

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`.



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?).

11 Reflection

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