Econ771 - Empirical Exercise 1

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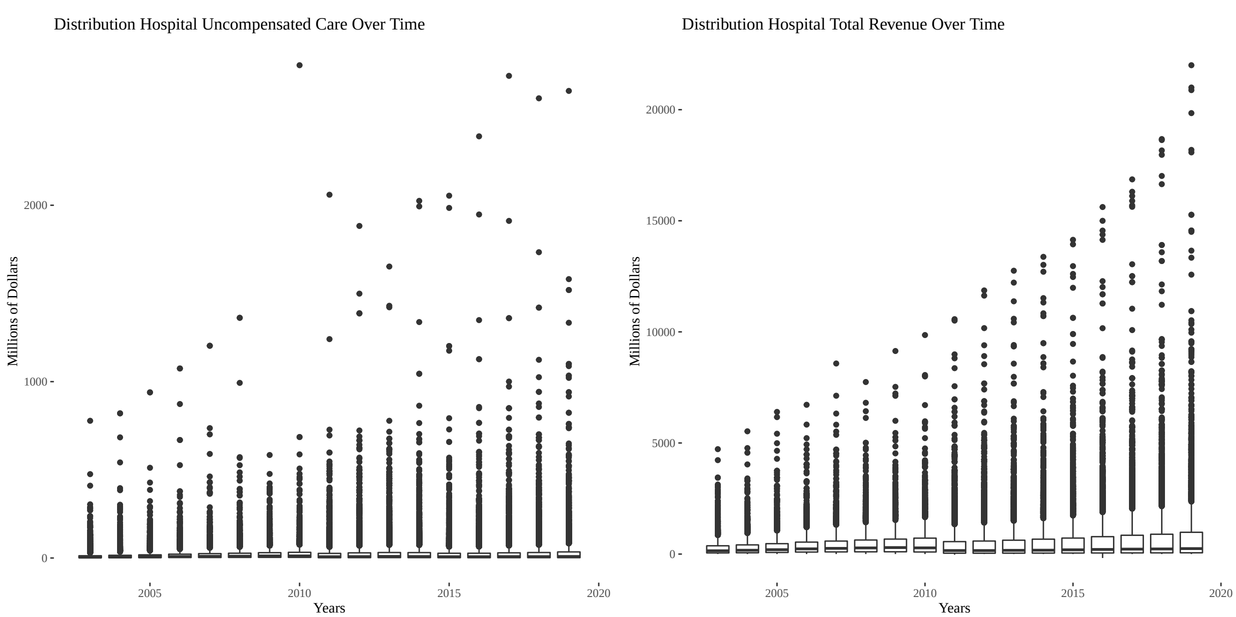
Summary Statistics

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. We start first by downloading and merging all the Data from the Github repository. We present the distribution of the variables of interest, Uncompensated care and Hospital Revenue over time



(a) Uncompensated Care

(b) Revenue

Figure 1: Box-plot

We see evidence of negative entries in uncompensated care as well as extreme atypical values that might be caused by mistyping. As such, we subset the data by not including the top and bottom 0.5% of the observations. The mean, standard deviation, and minimum and maximum values across the years are presented in table 1 of summary statistics.

Table 1: Hospital Summary Statistics

	Uncompensated Care				Total Revenue			
year	Mean	Sd	Min	Max	Mean	Sd	Min	Max
2003	13.57	32.05	0	777.99	292.35	397.70	1.66	4722.76
2004	15.33	36.66	0	820.25	327.69	445.42	0.27	5525.73
2005	17.41	37.81	0	939.13	380.14	514.68	1.14	6398.55
2006	20.97	47.16	0	1074.62	433.73	558.58	1.33	6718.17
2007	23.56	51.28	0	1203.37	484.24	646.76	0.99	8577.05
2008	26.43	57.06	0	1361.81	513.43	655.58	0.97	7743.08
2009	27.44	46.42	0	583.98	552.80	718.35	0.89	9139.32
2010	29.89	72.41	0	2793.92	576.62	779.98	0.84	9857.53
2011	26.82	63.17	0	2059.70	480.04	776.84	-27.58	10572.29
2012	29.87	72.54	0	1882.62	505.10	830.36	0.85	11865.32
2013	31.93	72.63	0	1652.58	539.20	903.93	0.95	12751.71
2014	31.79	77.39	0	2024.85	577.45	980.59	1.09	13376.35
2015	29.83	74.67	0	2054.15	623.38	1048.30	1.05	14143.53
2016	31.14	80.95	0	2390.67	677.54	1157.37	-177.03	15618.75
2017	33.38	87.36	0	2733.60	727.36	1263.39	1.00	16863.43
2018	35.90	90.49	0	2606.35	782.42	1386.47	1.07	18677.25
2019	39.82	99.48	0	2648.26	855.33	1538.23	0.72	22000.93
2003-2019	28.77	71.96	0	2793.92	574.79	993.11	-177.03	22000.93

Next, we create a figure showing the mean hospital uncompensated care from 2003 to 2019. We show this trend separately by hospital ownership type in figure 3. We present an smooth trend to easily identify shifts after the adoption of medicare expansion in 2014. We can see an abrupt bump from years 2010 to 2011, this might be due to the adoption of the new form and a change in the way to measure uncompensated care ^[after 2010 uncompensated care = total uncompensated care - total uncompensated partial payments + bad debt]. Also, in recent years, it seems for-profit hospitals get to provide more uncompensated care than not for profit hospitals.

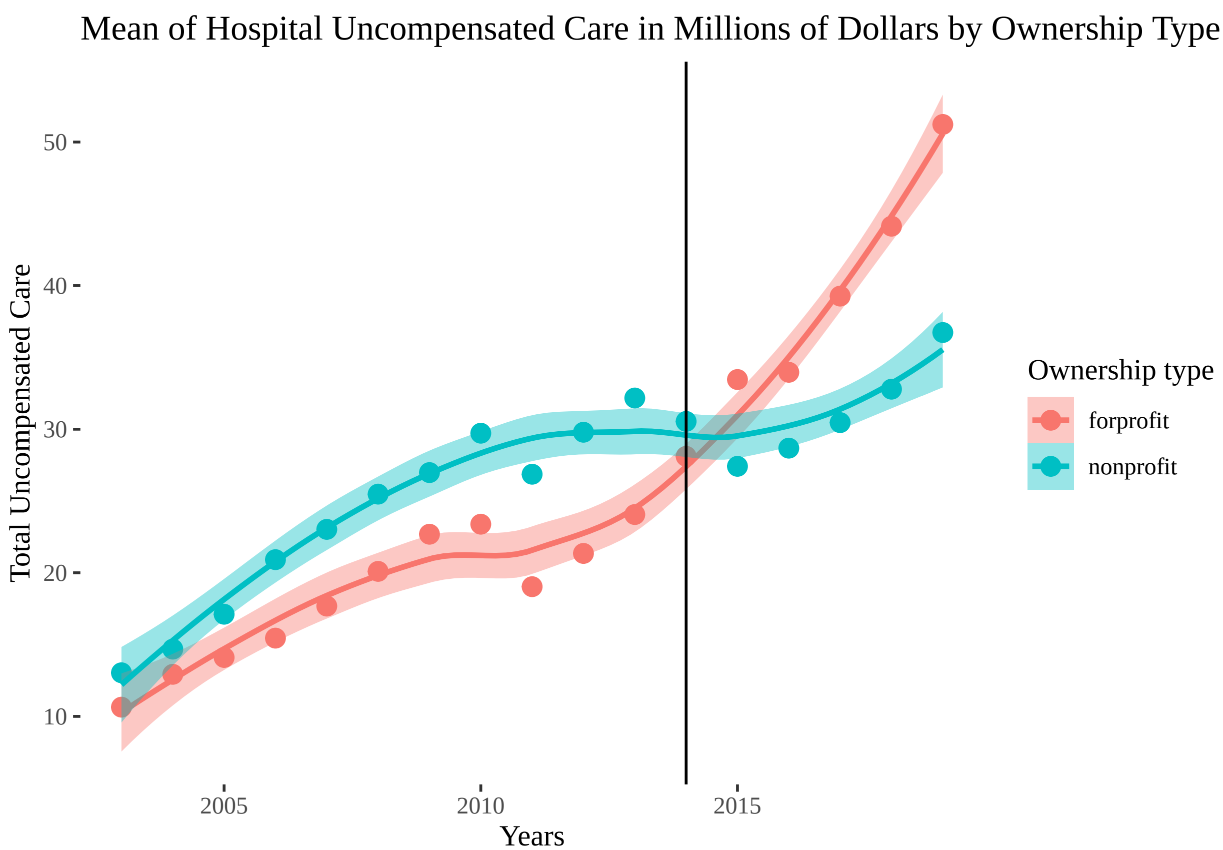


Figure 2: Evolution of Uncompensated Care Over Time

Table 2: Two Way Fixed Effects

	1	2	3	4
Treatment	-28.363***	-31.518***	-12.173***	-12.153***
	(1.893)	(2.185)	(1.848)	(1.550)
Num.Obs.	79557	69824	74768	77624
R2	0.699	0.708	0.690	0.691
RMSE	38.21	38.97	39.48	38.91
Std.Errors	by: pn	by: pn	by: pn	by: pn

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

TWFE Specification

Using a simple DD identification strategy, we 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. We present four estimates from this estimation in table **??**: one based on the full sample (1); one when limiting to the 2014 treatment group (2); one when limiting to the 2015 treatment group (3); and one when limiting to the 2016 treatment group (3).

A first appreciation of our results indicate that the ATE of medicaid expansion on uncompensated care is negative. The point estimate varies when limiting the treatment sample for 2014 to 2016 as well as the confidence intervals but we get a consistent trend across the samples. We see the effect is larger when limiting the sample to the states that expanded in 2014.

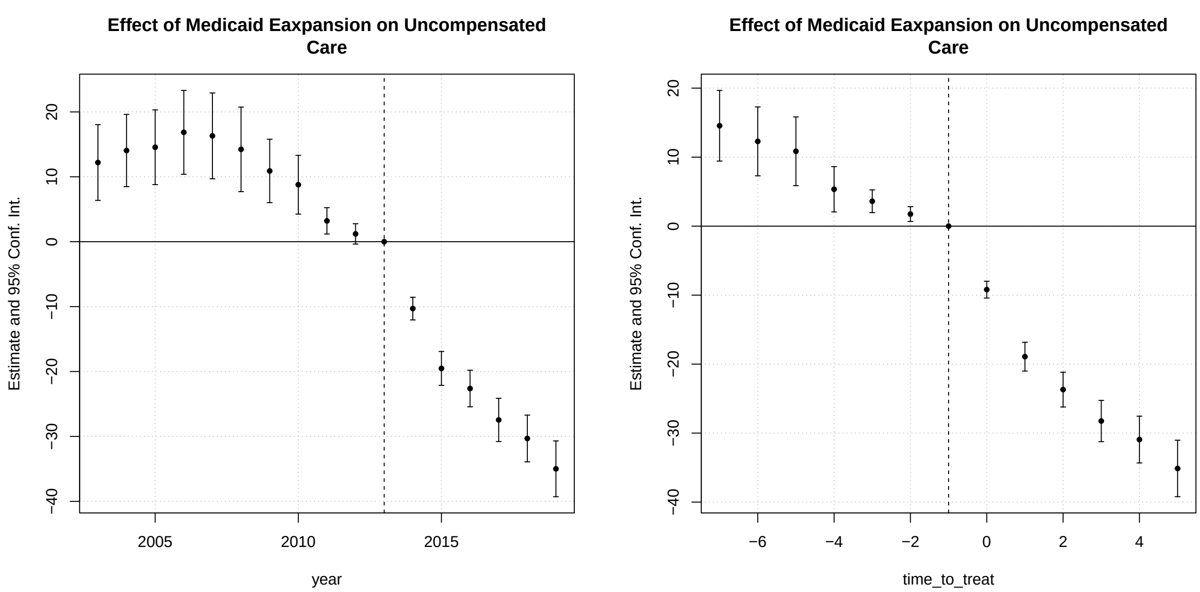
Event Study Specification

We 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 an interaction between the treatment indicator and a relative time indicator. τ denotes years relative to Medicaid expansion. In this case $\tau = -1$ denotes the year before a state expanded Medicaid and the control group for those never treated. $\tau = 0$ denotes the year of expansion, and so on.

Table **??** presents the estimates for the common treatment time for the 2014 sample, whereas **??** presents the estimates for the staggered intervention for the full sample. In both specifications the control group is formed by the never treated. Also, we can observe in **??** the event study coefficients plot. It is clear the drop in uncompensated care after the first year of the medicaid expansion. Also the ATT seems to increase as τ increases. We can see that the average treatment on the treated is the highest 5 years after the treatment.



(a) Sample 2014 (b) Full Sample

Figure 3: Event Study

Table 3: Event Study Sample 2014

	Model 1
year = 2003 × treated	12.199***
	(2.978)
year = 2004 × treated	14.048***
	(2.840)
year = 2005 × treated	14.556***
	(2.936)
year = 2006 × treated	16.852***
	(3.294)
year = 2007 × treated	16.307***
	(3.373)
year = 2008 × treated	14.229***
	(3.324)
year = 2009 × treated	10.901***
	(2.492)
year = 2010 × treated	8.781***
	(2.309)
year = 2011 × treated	3.213**
	(1.033)
year = 2012 × treated	1.204
	(0.797)
year = 2014 × treated	-10.301***
	(0.892)
year = 2015 × treated	-19.522***
	(1.331)
year = 2016 × treated	-22.619***
	(1.438)
year = 2017 × treated	-27.455***
	(1.700)
year = 2018 × treated	-30.317***
	(1.838)
year = 2019 × treated	-34.989***
	(2.191)
Num.Obs.	69824
RMSE	38.82
Std.Errors	by: pn
FE: pn	X
FE: year	X

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

Table 4: Event Estudy Full Sample

	Model 1
time_to_treat = -7 × treated	14.553***
	(2.611)
time_to_treat = -6 × treated	12.287***
	(2.547)
time_to_treat = -5 × treated	10.850***
	(2.542)
time_to_treat = -4 × treated	5.346**
	(1.674)
time_to_treat = -3 × treated	3.606***
	(0.842)
time_to_treat = -2 × treated	1.750**
	(0.548)
time_to_treat = 0 × treated	-9.201***
	(0.622)
time_to_treat = 1 × treated	-18.916***
	(1.067)
time_to_treat = 2 × treated	-23.692***
	(1.287)
time_to_treat = 3 × treated	-28.244***
	(1.526)
time_to_treat = 4 × treated	-30.934***
	(1.730)
time_to_treat = 5 × treated	-35.122***
	(2.088)
Num.Obs.	79557
RMSE	38.02
Std.Errors	by: pn
FE: pn	X
FE: year	X

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

SA Specification

No we move to Sun and Abraham(SA) specification and estimate a non-conxvex average of all other group-time specific average treatment effects. The interaction weighted specification is given by:

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

?? presents the Re-estimate coefficients for the event study using the SA specification. For this specification we focus on the states that expanded either on 2014, 2015 or 2016 and include those in the treatment group. Whereas the control group is formed by the never treated observations. Providers that are in a state that expanded after 2016 are not considered in this part. The coefficients presented in the table are $\hat{\delta}_{e,\tau}$.

Also, **??** presents the coefficients plot for the SA specification. We can see how this smooth the pre-trend before the medicaid expansion. Under this especification we see the Uncompensated care is significatly declining even before the expansion.

Table 5: Event Estudy SA Specification

	Model 1
time_to_treat = -7	15.552***
	(2.563)
time_to_treat = -6	14.639***
	(2.875)
time_to_treat = -5	12.228***
	(2.528)
time_to_treat = -4	7.590***
	(1.767)
time_to_treat = -3	3.401***
	(0.895)
time_to_treat = -2	1.638**
	(0.634)
time_to_treat = 0	-9.411***
	(0.723)
time_to_treat = 1	-18.360***
	(1.129)
time_to_treat = 2	-22.200***
	(1.280)
time_to_treat = 3	-26.974***
	(1.528)
time_to_treat = 4	-29.782***
	(1.729)
time_to_treat = 5	-34.456***
	(2.107)
Num.Obs.	79557
RMSE	38.00
Std.Errors	by: pn
FE: pn	X
FE: year	X

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

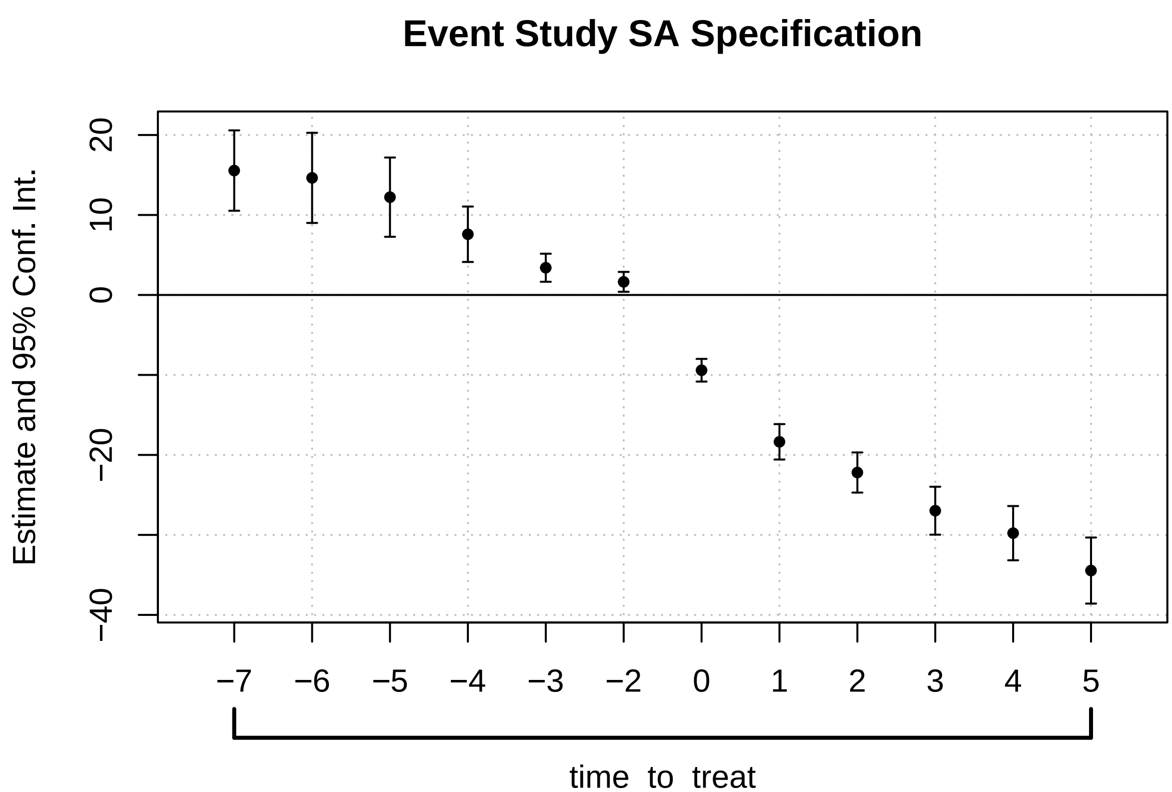
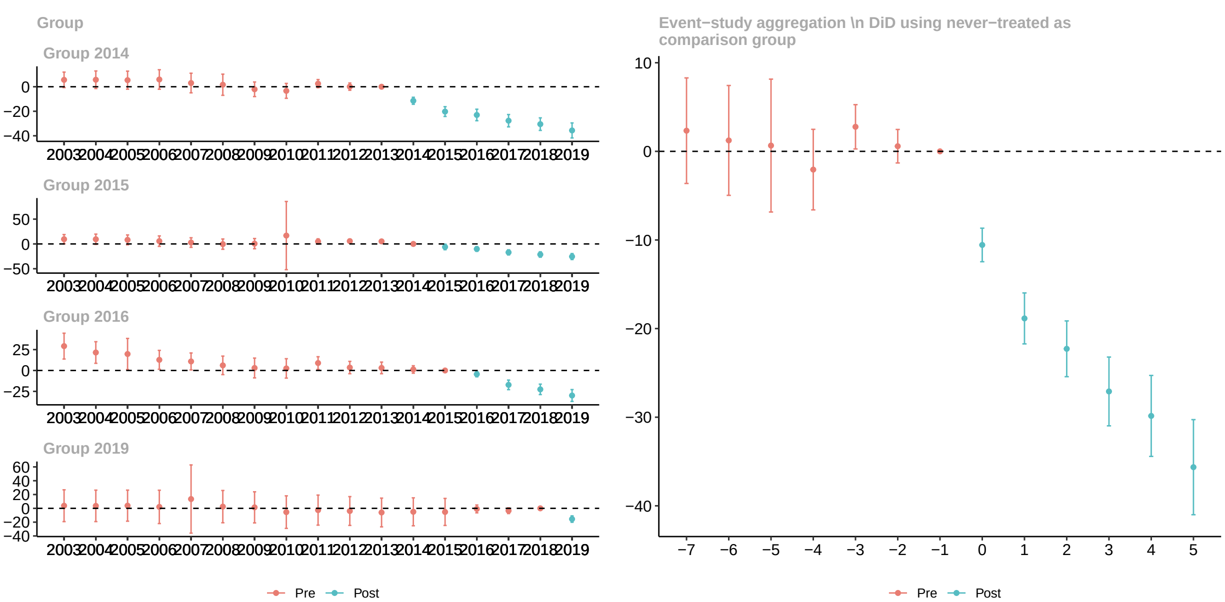


Figure 4: Effect of Medicaid Eaxpansion on Uncompensated - SA Specification

CS Specification

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`.



(a) ATT by Cohorts

(b) Event Study

Figure 5: CS Specification

Table 6: DiD CS Specification

	Model 1
ATT(2014,2003)	5.619
	(2.063)
ATT(2014,2004)	5.711
	(2.336)
ATT(2014,2005)	5.374
	(2.399)
ATT(2014,2006)	5.922
	(2.593)
ATT(2014,2007)	3.030
	(2.611)
ATT(2014,2008)	1.638
	(2.818)
ATT(2014,2009)	-2.067
	(1.941)
ATT(2014,2010)	-3.365
	(1.980)
ATT(2014,2011)	2.530
	(1.088)
ATT(2014,2012)	0.090
	(0.965)
ATT(2014,2013)	0.000
ATT(2014,2014)	-11.446
	(0.934)
ATT(2014,2015)	-20.250
	(1.297)
ATT(2014,2016)	-23.016
	(1.531)
ATT(2014,2017)	-27.688
	(1.641)
ATT(2014,2018)	-30.492
	(1.667)
ATT(2014,2019)	-35.639
	(1.998)
ATT(2015,2003)	9.581
	(3.039)
ATT(2015,2004)	9.444
	(3.370)
ATT(2015,2005)	8.175
	(3.245)
ATT(2015,2006)	5.645
	(3.437)
ATT(2015,2007)	2.815
	(3.139)
ATT(2015,2008)	-0.399
	(3.374)
ATT(2015,2009)	0.605
	(3.361)

Table 7: Event Estudy CS Specification

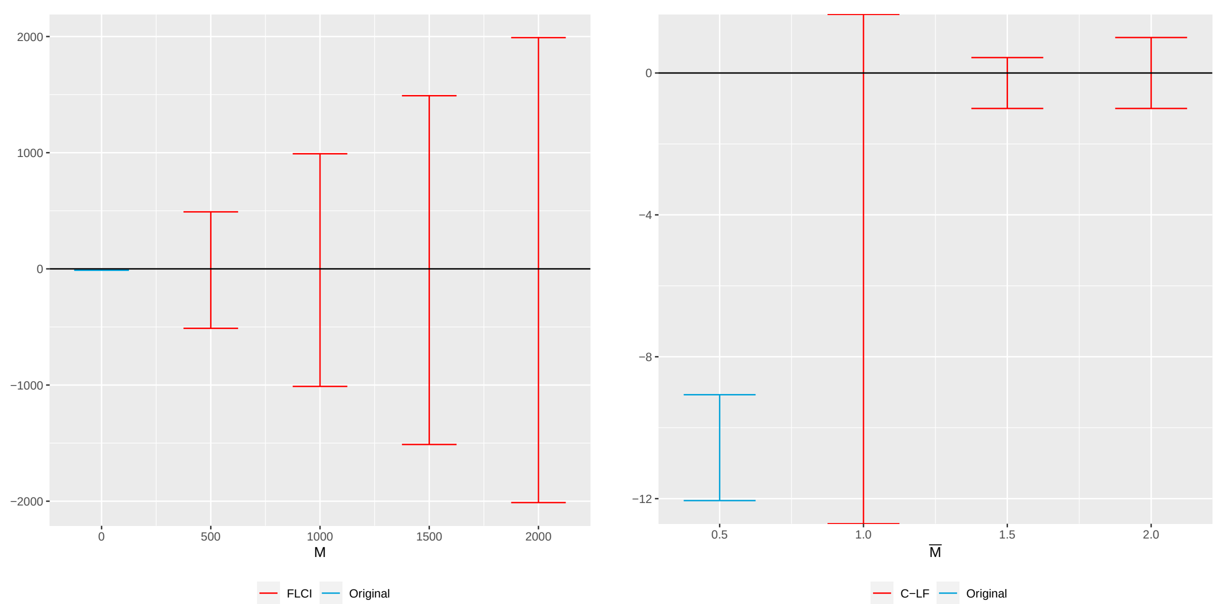
	Model 1
ATT(-7)	2.333
	(2.289)
ATT(-6)	1.235
	(2.382)
ATT(-5)	0.653
	(2.882)
ATT(-4)	-2.060
	(1.747)
ATT(-3)	2.769
	(0.961)
ATT(-2)	0.581
	(0.726)
ATT(-1)	0.000
ATT(0)	-10.562
	(0.727)
ATT(1)	-18.852
	(1.105)
ATT(2)	-22.281
	(1.209)
ATT(3)	-27.093
	(1.492)
ATT(4)	-29.855
	(1.756)
ATT(5)	-35.639
	(2.062)
Num.Obs.	5815
Std.Errors	by: pn_id
type	dynamic
ngroup	4.000
ntime	17.000
control.group	nevertreated
est.method	dr

RR Specification

Rambachan and Roth (RR) show that traditional tests of parallel pre-trends may be under-powered, 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 violation is reflected by

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

Using the `HonestDiD` package in `R` or `Stata`, present a sensitivity plot of your CS ATT estimates using $\bar{M} = \{0, 0.5, 1, 1.5, 2\}$. Check out the GitHub repo here for some help in combining the `HonestDiD` package with CS estimates.



(a) Smooth (b) Sensitivity

Figure 6: RR Specification

Discussion

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?).

Across all different specifications we see a robust result, the ATE is negative, that is the reduction in Uncomponsetad Care provided by hospitals is due to the exogenous policy shock, the expansion Medicaid across states. We have robust evidence to say this is a cusal effect.

Reflection

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

The first challenge was to collect all data sets and merge them into one, which requires a few programming skills and institutional knowledge of the field. I encountered one specific problem while combining POS and HCRIS data since I was not aware of the possibility that providers changed the ownership compositions over time. I was not aware of this situation until very late.

A second challenge was implementing the HonestDiD package. My results were not interpretable or plausible when dealing with the original grid.

I can get two main takeaways from this assignment. The importance of developing a transparent and reproducible workflow allowed me to make the changes easily) and improve my coding skills to avoid code repetition and improve accuracy and efficiency.