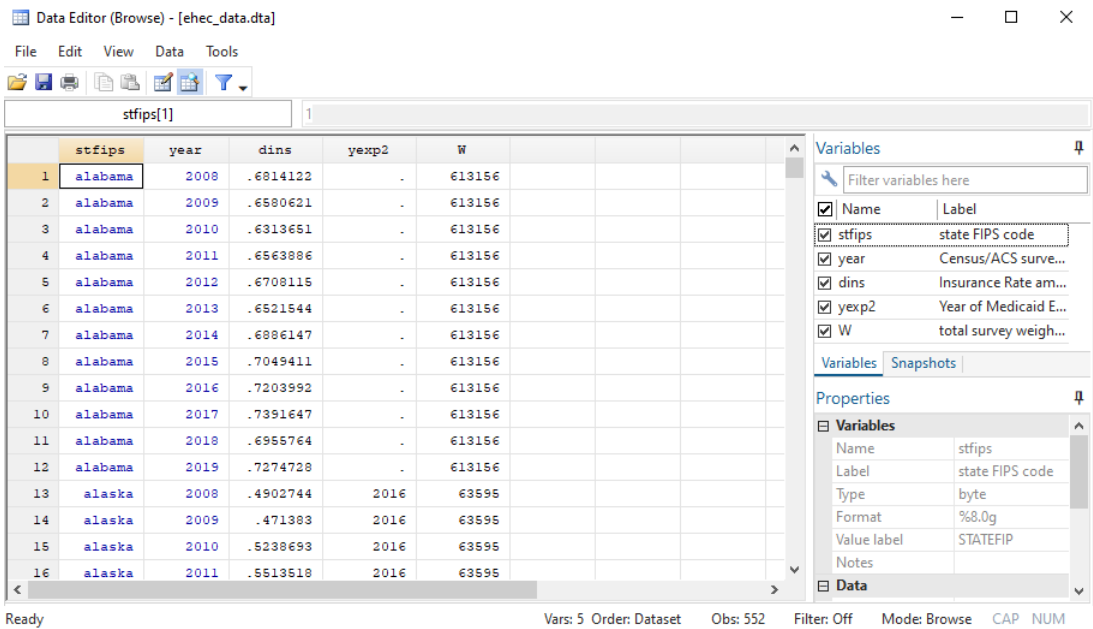


Econometrics Assignment 5

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Question 1

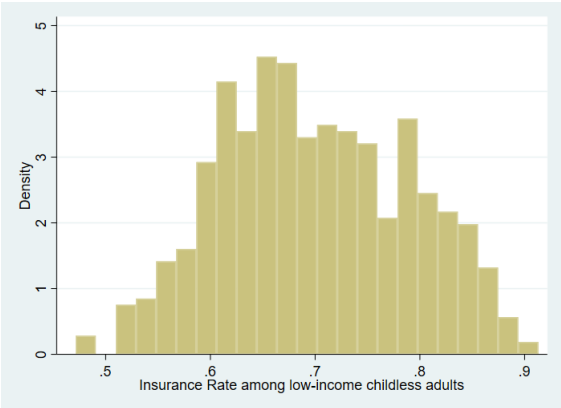
(a)



(b) & (c)

```
. tab year
```

Census/ACS survey year	Freq.	Percent	Cum.
2008	46	8.33	8.33
2009	46	8.33	16.67
2010	46	8.33	25.00
2011	46	8.33	33.33
2012	46	8.33	41.67
2013	46	8.33	50.00
2014	46	8.33	58.33
2015	46	8.33	66.67
2016	46	8.33	75.00
2017	46	8.33	83.33
2018	46	8.33	91.67
2019	46	8.33	100.00
Total	552	100.00	



For 2008-2019, data is available.

(d)

```
. tab yexp2 if year==2008, missing
```

Year of Medicaid Expansion	Freq.	Percent	Cum.
2014	22	47.83	47.83
2015	3	6.52	54.35
2016	2	4.35	58.70
2017	1	2.17	60.87
2019	2	4.35	65.22
.	16	34.78	100.00
Total	46	100.00	

```
. codebook stfips
```

stfips	state FIPS code
type: numeric (byte)	
label: STATEFIP	
range: [1,56]	units: 1
unique values: 46	missing .: 0/552
examples: 15 hawaii	
24 maryland	
34 new jersey	
45 south carolina	

In the data, 22 states expanded in 2014. 16 never expanded.
stfips has 46 unique values, which means that it has data from 46 states, thus not all 50 states are contained in the data.

(e)

drop if yexp2 == 2015
gen treatment = 0
replace treatment = 1 if yexp2 <= 2014

. tab treatment if year==2008, missing

treatment	Freq.	Percent	Cum.
0	21	48.84	48.84
1	22	51.16	100.00
Total	43	100.00	

46-3=43, so the number is right

(f)

. bysort year treatment: sum dins

-> year = 2008, treatment = 0					
Variable	Obs	Mean	Std. dev.	Min	Max
dins	21	.6296928	.0620747	.4902744	.7352178
-> year = 2008, treatment = 1					
Variable	Obs	Mean	Std. dev.	Min	Max
dins	22	.6640828	.0589791	.5710957	.7850013
-> year = 2009, treatment = 0					
Variable	Obs	Mean	Std. dev.	Min	Max
dins	21	.6186757	.066622	.471383	.7457104
-> year = 2009, treatment = 1					
Variable	Obs	Mean	Std. dev.	Min	Max
dins	22	.6470537	.0608332	.5450087	.7717041
-> year = 2010, treatment = 0					
Variable	Obs	Mean	Std. dev.	Min	Max
dins	21	.6096694	.0556358	.5184326	.7033234

bysort year treatment: sum dins gives a very bad table so I'm using another one.

. tab year if treatment==1, sum(dins)

Census/ACS survey year	Summary of Insurance Rate among low-income childless adults		
	Mean	Std. Dev.	Freq.
2008	.66408277	.05897912	22
2009	.64705367	.06083315	22
2010	.64666867	.06107716	22
2011	.64950643	.06294438	22
2012	.65703935	.06449358	22
2013	.66242208	.05845086	22
2014	.75371452	.05418906	22
2015	.8080168	.04312584	22
2016	.82896771	.04356355	22
2017	.82087042	.04192338	22
2018	.8204765	.03987981	22
2019	.81819207	.03942364	22
Total	.73141758	.09490569	264

. tab year if treatment==0, sum(dins)

Census/ACS survey year	Summary of Insurance Rate among low-income childless adults		
	Mean	Std. Dev.	Freq.
2008	.62969285	.06207466	21
2009	.61867571	.06662203	21
2010	.60966938	.05563584	21
2011	.61125046	.05444716	21
2012	.61702441	.05897054	21
2013	.6227468	.04490705	21
2014	.66759239	.05465418	21
2015	.69913534	.04614653	21
2016	.7145581	.04496555	21
2017	.71698077	.050089	21
2018	.7189196	.05063796	21
2019	.71389971	.05309046	21
Total	.66167879	.06974533	252

(g)

Change in average insurance rate for non-treated: 0.66759239-0.6227468 = 0.04484559
Change in average insurance rate for treated: 0.75371452-0.66242208 = 0.09129244
DID estimate = 0.09129244 - 0.04484559 = 0.04644685

(h)

gen t2014=0
replace t2014 = 1 if year==2014
gen treatx2014=treatment*t2014
gen filter = 0
replace filter = 1 if year==2014 | year==2013

```
. regress dins t2014 treatment treatx2014 if filter==1, cluster(stfips)
```

Linear regression	Number of obs	=	86
	F(3, 42)	=	96.65
	Prob > F	=	0.0000
	R-squared	=	0.4586
	Root MSE	=	.05336

(Std. Err. adjusted for 43 clusters in stfips)

dins	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
t2014	.0448456	.0060665	7.39	0.000	.0326029 .0570883
treatment	.0396753	.0159493	2.49	0.017	.0074883 .0718622
treatx2014	.0464469	.0091256	5.09	0.000	.0280306 .0648631
_cons	.6227468	.009852	63.21	0.000	.6028648 .6426289

β_3 is the same as the DID estimate I calculated earlier.

(i)

Parallel trends assumption assumes that the difference between treatment group and control group should be constant with the absence of treatment.

$$\mu_{1,2014}^0 - \mu_{1,2013}^0 = \mu_{0,2014}^0 - \mu_{0,2013}^0 \tag{1}$$

$$E[Y_{i2014}(0) - Y_{i2013}(0)|D_i = 1] = E[Y_{i2014}(0) - Y_{i2013}(0)|D_i = 0] \tag{2}$$

In this case, it means that the difference between the dins estimates for states in the treatment group and that of control group should be (approximately) the same without the treatment, which is "before 2014" in this case.

(j)

```
drop t2014
tabulate year, generate(year)
ren year# year#, renumber(2008)

quietly forval j = 2008/2019 {
    generate t`j' = treatment * year`j'
}
replace t2013 = 0

regress dins i.year i.stfips t2*, cluster(stfips)
ssc install coefplot
coefplot, omitted keep(t2*) vertical
```

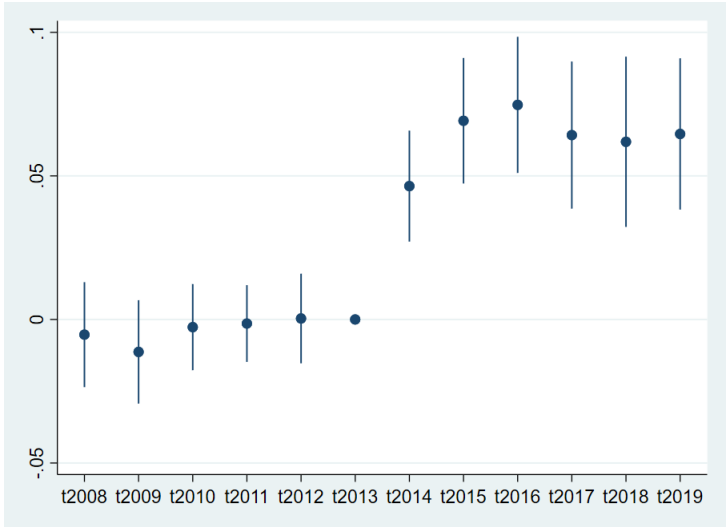
```
. regress dins i.year i.stfips t2*, cluster(stfips)
note: t2013 omitted because of collinearity.
```

Linear regression	Number of obs	=	516
	F(21, 42)	=	.
	Prob > F	=	.
	R-squared	=	0.9374
	Root MSE	=	.0242

(Std. err. adjusted for 43 clusters in stfips)

dins	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]
year					
2009	-.0110171	.0041383	-2.66	0.011	-.0193686 -.0026657
2010	-.0200235	.0049124	-4.08	0.000	-.0299371 -.0101098
2011	-.0184424	.0054814	-3.36	0.002	-.0295044 -.0073804
2012	-.0126684	.0043538	-2.91	0.006	-.0214547 -.0038822
2013	-.006946	.0064585	-1.08	0.288	-.0199798 .0060877
2014	.0378995	.0042739	8.87	0.000	.0292745 .0465246
2015	.0694425	.0081728	8.50	0.000	.0529492 .0859358
2016	.0848653	.0089196	9.51	0.000	.0668648 .1028657
2017	.0872879	.0101555	8.60	0.000	.0667932 .1077827
2018	.0892268	.0118061	7.56	0.000	.0654011 .1130525
2019	.0842069	.0117343	7.18	0.000	.0605261 .1078876
stfips					
alaska	-.103853	1.02e-15	-1.0e+14	0.000	-.103853 -.103853
arizona	-.0412094	.0067381	-6.12	0.000	-.0548075 -.0276113
arkansas	-.0117976	.0067381	-1.75	0.087	-.0253957 .0018005
california	-.0416807	.0067381	-6.19	0.000	-.0552788 -.0280825
colorado	-.0107549	.0067381	-1.60	0.118	-.024353 .0028433
connecticut	.0482399	.0067381	7.16	0.000	.0346418 .061838
florida	-.0857497	1.02e-15	-8.4e+13	0.000	-.0857497 -.0857497
georgia	-.090137	1.02e-15	-8.9e+13	0.000	-.090137 -.090137
hawaii	.1102658	.0067381	16.36	0.000	.0966677 .1238639

idaho	-.0128005	1.02e-15	-1.3e+13	0.000	-.0128005	-.0128005
illinois	-.0163106	.0067381	-2.42	0.020	-.0299087	-.0027125
iowa	.0876154	.0067381	13.00	0.000	.0740173	.1012135
kansas	.0138945	1.02e-15	1.4e+13	0.000	.0138945	.0138945
kentucky	.0309765	.0067381	4.60	0.000	.0173784	.0445747
louisiana	-.0358099	1.02e-15	-3.5e+13	0.000	-.0358099	-.0358099
maine	.0656128	1.02e-15	6.4e+13	0.000	.0656128	.0656128
maryland	.0118266	.0067381	1.76	0.087	-.0017715	.0254247
michigan	.0349109	.0067381	5.18	0.000	.0213128	.048509
minnesota	.0884664	.0067381	13.13	0.000	.0748682	.1020645
mississippi	-.0424017	1.02e-15	-4.2e+13	0.000	-.0424017	-.0424017
missouri	.0185215	1.02e-15	1.8e+13	0.000	.0185215	.0185215
montana	.0016449	1.02e-15	1.6e+12	0.000	.0016449	.0016449
nebraska	.0465129	1.02e-15	4.5e+13	0.000	.0465129	.0465129
nevada	-.0688877	.0067381	-10.22	0.000	-.0824858	-.0552896
new jersey	-.0539224	.0067381	-8.00	0.000	-.0675205	-.0403243
new mexico	-.035146	.0067381	-5.22	0.000	-.0487441	-.0215479
north carolina	-.0214531	1.02e-15	-2.1e+13	0.000	-.0214531	-.0214531
north dakota	.0414656	.0067381	6.15	0.000	.0278675	.0550637
ohio	.0163148	.0067381	2.42	0.020	.0027167	.0299129
oklahoma	-.0662598	1.02e-15	-6.5e+13	0.000	-.0662598	-.0662598
oregon	-.0007891	.0067381	-0.12	0.907	-.0143872	.012809
rhode island	.0601783	.0067381	8.93	0.000	.0465801	.0737764
south carolina	-.0346476	1.02e-15	-3.4e+13	0.000	-.0346476	-.0346476
south dakota	.0173781	1.02e-15	1.7e+13	0.000	.0173781	.0173781
tennessee	-.0172016	1.02e-15	-1.7e+13	0.000	-.0172016	-.0172016
texas	-.1207823	1.02e-15	-1.2e+14	0.000	-.1207823	-.1207823
utah	-.0098695	1.02e-15	-9.7e+12	0.000	-.0098695	-.0098695
virginia	.0046849	1.02e-15	4.6e+12	0.000	.0046849	.0046849
washington	.0179123	.0067381	2.66	0.011	.0043142	.0315104
west virginia	.0310248	.0067381	4.60	0.000	.0174267	.044623
wisconsin	.0494254	.0067381	7.34	0.000	.0358273	.0630235
wyoming	-.0281642	1.02e-15	-2.8e+13	0.000	-.0281642	-.0281642
t2008	-.0052854	.0090566	-0.58	0.563	-.0235622	.0129915
t2009	-.0112973	.0089213	-1.27	0.212	-.0293013	.0067066
t2010	-.002676	.0074388	-0.36	0.721	-.017688	.012336
t2011	-.0014193	.0066217	-0.21	0.831	-.0147825	.0119439
t2012	.0003397	.0077351	0.04	0.965	-.0152705	.0159498
t2013	0	(omitted)				
t2014	.0464469	.009578	4.85	0.000	.0271176	.0657761
t2015	.0692062	.010832	6.39	0.000	.0473463	.091066
t2016	.0747343	.0117466	6.36	0.000	.0510288	.0984399
t2017	.0642144	.012695	5.06	0.000	.0385948	.0898339
t2018	.0618816	.0146892	4.21	0.000	.0322376	.0915256
t2019	.0646171	.0130541	4.95	0.000	.0382728	.0909614
_cons	.6535443	.0051142	127.79	0.000	.6432234	.6638652



(k)

$\hat{\beta}_{2014}$ is the same as the DID calculated above. $\hat{\beta}_{2012}$ is .0003397, which is the DID for year 2011-2012, which can be represented as:

$$\hat{\beta}_{2012} = (\bar{Y}_{1,2013} - \bar{Y}_{1,2012}) - (\bar{Y}_{0,2013} - \bar{Y}_{0,2012}) \tag{3}$$

$$= (\bar{Y}_{1,2013} - \bar{Y}_{0,2013}) - \bar{Y}_{1,2012} + \bar{Y}_{0,2012} \tag{4}$$

$\hat{\beta}$ is an interaction term of treatment and year that gives out each year's DID when compared to the previous year.

(l)

```
. test t2008 t2009 t2010 t2011 t2012

( 1)  t2008 = 0
( 2)  t2009 = 0
( 3)  t2010 = 0
( 4)  t2011 = 0
( 5)  t2012 = 0

F( 5, 42) = 0.76
Prob > F = 0.5856
```

In this case we fail to reject the null hypothesis that pre-treatment event-study coefficients all equal to 0. This

boosts my confidence in parallel trends assumption because it show that there's no significant interactive effects between treatment and year prior to treatment year.

(m)

Post-treatment coefficients are larger than pre-treatment coefficients in general and we can not draw a straight line. It boosts my confidence because it shows that there's real difference before and after treatment in coefficients.

(n)

No. I still can draw a straight line, which means that the difference between pre/post-treatment coefficients is not large.

(o)

The confounding variables are possible covariates that changes over time in treatment and control group. For example, if there's strict insurance mandate policies passed during 2008-2014, it will drive the insurance rate up, but not as a possible effect of medicaid expansion.