

# Method HW2

MAX WANG

February 18, 2020

## Part I. Redo the job interview table

I rewrote a lot of codes. Here is a screenshot of beginning part of the changes.

```

@@ -1,12 +1,15 @@
1 1 // Assignment #1
2 2 // Assignment #2
3 3 // Max Wang
4 4 // YN2636
5 5 // Feb, 2020
6 6
7 7 -cd "/Users/yn2636/Google Drive/Spring2020/method/tern2/HM1"
8 8 +
9 9 +// PART I.
10 10
11 11 -cd "/Users/yn2636/Google Drive/Spring2020/method/tern2/HM2"
12 12
13 13
14 14 * Read in data:
15 15 -insheet using "working.folder/assignment1-research-methods.csv", tab names clear
16 16 +insheet using "assignment1-research-methods.csv", tab names clear
17 17
18 18
19 19 * Label your variables
20 20 label variable candidateid "ID"
21 21
22 22 @@ -32,77 +35,113 @@ callbacks.
23 23
24 24
25 25 * Run regression:
26 26 est clear
27 27
28 28
29 29 ** univariate
30 30 -qui reg callback 1.eliteschoolcandidate
31 31
32 32 *** baseline model
33 33 -qui reg callback 1.eliteschoolcandidate 1.bigcompanycandidate recruiteriswhite recruiterismale
34 34 +margins, dydx(1.eliteschoolcandidate 1.bigcompanycandidate) post
35 35
36 36
37 37 eststo e1s1
38 38
39 39 -qui logit callback 1.eliteschoolcandidate
40 40 +qui logit callback 1.eliteschoolcandidate 1.bigcompanycandidate recruiteriswhite recruiterismale
41 41 +margins, dydx(1.eliteschoolcandidate 1.bigcompanycandidate) post
42 42
43 43
44 44

```

Below is the new table of results with and without male candidacy.

Table 1: Marginal Effects of Elite Schoole, Bigfirm and Male Candidacy on Interview Callback Rate

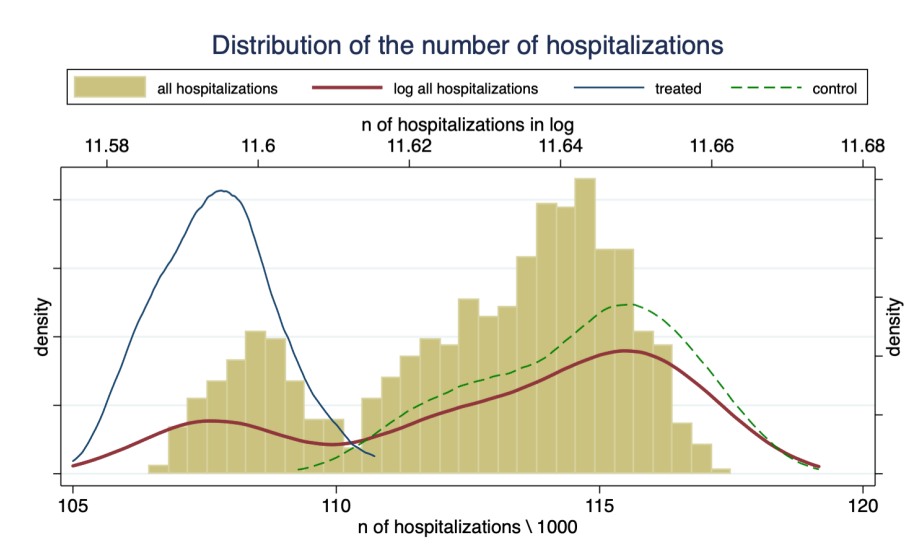
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	ClusteredSE	Logit	Logit	ClusteredSE
EliteSch=1	.14*** (.032)	.14*** (.032)	.2*** (.064)	.14*** (.031)	.14*** (.031)	.19*** (.059)
BigComp=1	.09*** (.032)	.09*** (.032)	.16** (.069)	.09*** (.031)	.09*** (.031)	.14** (.062)
MaleApp=1		-.044 (.032)	-.044 (.046)		-.044 (.032)	-.044 (.045)
EliteSchXBigComp			-.13 (.091)			-.12 (.089)
Observations	864	864	864	864	864	864

Note: additional controls include recruiters' gender and race.

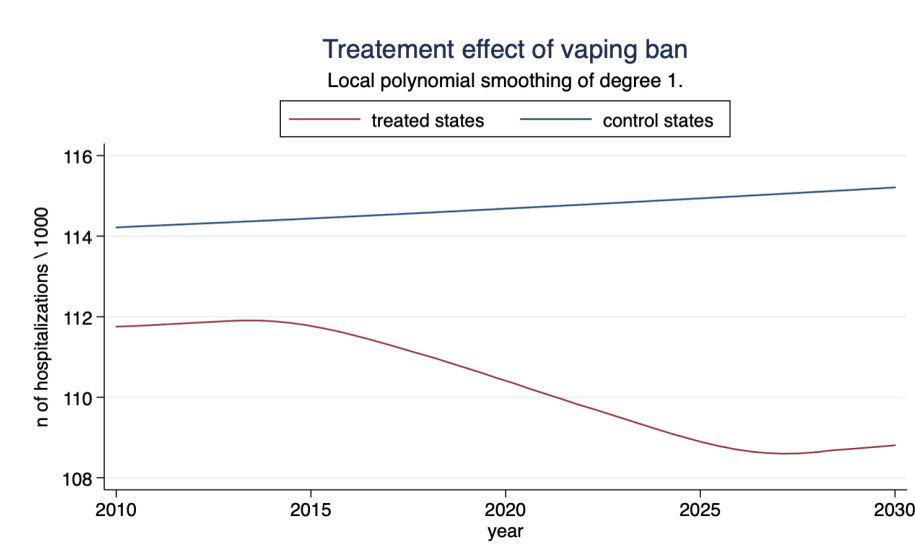
\*  $p < .10$ , \*\*  $p < .05$ , \*\*\*  $p < .01$

## Part II. The vaping bans

First, I use the figure below to choose my dependent variable. It shows that the total number of hospitalizations and its log follow a bi-modal distribution. Further breaking down the total number, it appears that two groups (i.e. treated and control) each follow a somewhat normal distributions. So it should be okay to just use the numbers as my dependent variable.



Second, I plot the canonical diff-in-diff plot. To smooth the lines I use the first degree local polynomial smoother. It shows that the treated states experience a drop in the number of hospitalizations after the ban in 2021, which echoes the distributions in the first figure.



The final task is to retrieve the diff-in-diff estimators from regressions. I use four specifications: OLS, state fixed-effects, state- and year-fixed effects, and state-effects with year trends. Robust standard errors and adjusted r-squared are reported. I include year trend because the second figure shows some upward trend in the number of my dependent variable. Model (4) confirms this is the case. Regardless, the treatment effect is identified across all models.

Table 2: Diff-in-Diff Estimation of the Effect of Vaping Bans

	(1)	(2)	(3)	(4)
	RE	State FE	State-Year FE	State FE
Vaping.Ban	-5,365*** (79)	-3,509*** (51)	-4,030*** (66)	-4,045*** (59)
Year				51*** (3.3)
Constant	113,860*** (55)	113,454*** (22)	113,568*** (23)	10,534 (6,679)
Observations	1050	1050	1050	1050
Adjusted $R^2$	0.702	0.951	0.960	0.961

Note: robust standard errors in parantheses; state FEs are controlled in model (2)-(4).

\*  $p < .10$ , \*\*  $p < .05$ , \*\*\*  $p < .01$