Method HW2

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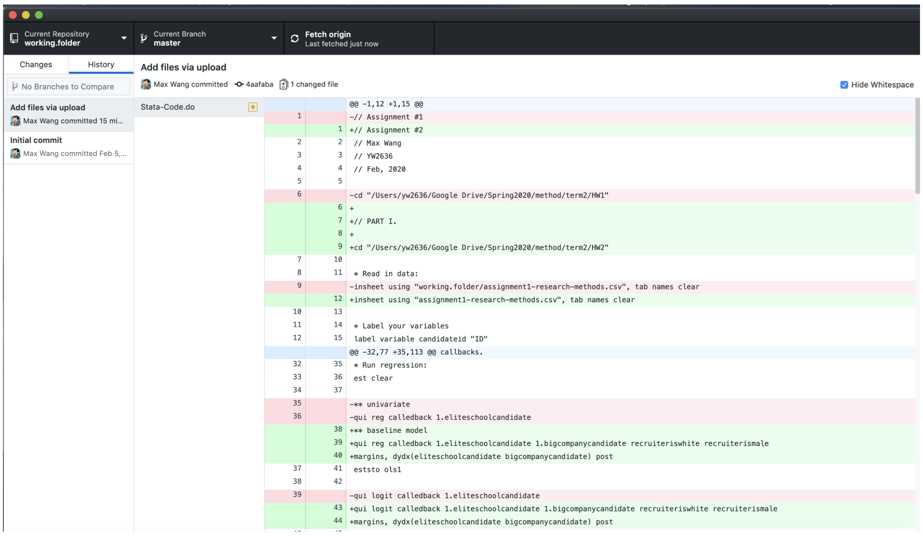
Part I. Redo the job interview table

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



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

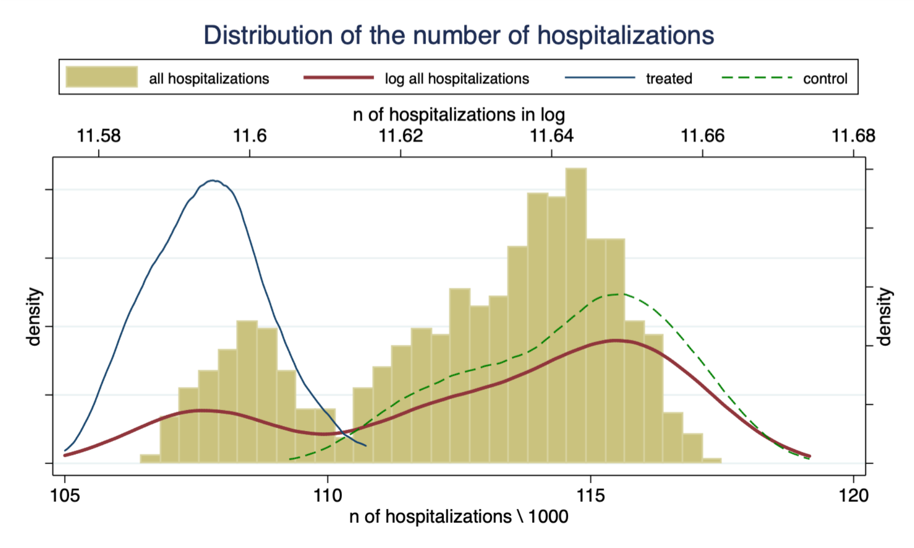
Table 1: Marginal Effects of Elite Schoole, Bigfirm and Male Candidacy on Interview Callback Rate

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

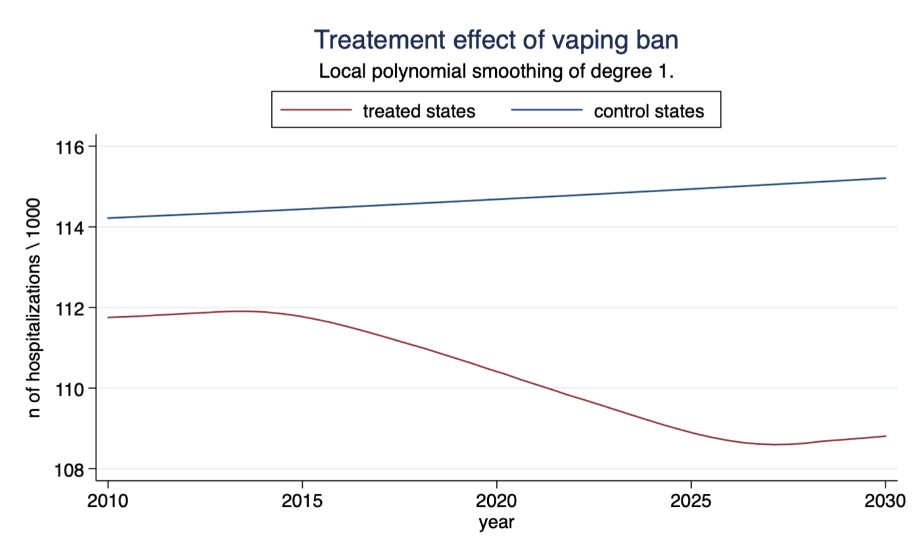
Note: additional controls include recruiters' gender and race.
* $p < .10$, ** $p < .05$, *** $p < .01$

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.

The first random-effects model sets the baseline. It shows the treatment decreases the number of hospitalizations by 5,365. Model (2) controls for state fixed-effects, and the average treatment effect drops to 3,509. Model (3) further controls for year fixed-effects, and the average treatment effect raises back to 4,030. This implies some underlying dynamics over the years that might have been absorbed by the constant, and it is in line with the the upward trend in the second figure above. Model (4) confirms this is the case, as the treatment effect is pretty much unchanged while an increasing trend in hospitalization is identified. Throughout, the key coefficient of average treatment effect is strong identified. As more controls are introduced, the models also explains the variation of hospitalization better measured by adjusted r-squared.

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

	(1)	(2)	(3)	(4)
		State	State-Year	State
	RE	FE	FE	FE
Vaping.Ban	-5,365***	-3,509***	-4,030***	-4,045***
	(79)	(51)	(66)	(59)
Year				51***
				(3.3)
Constant	113,860***	113,454***	113,568***	10,534
	(55)	(22)	(23)	(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).
* $p < .10$, ** $p < .05$, *** $p < .01$