

## **Assignment 5**

1. C
2. C D
3. D
4. A C
5. A C
6. A C
7. A B C D
8. B
9. C
10. A D
- 11.

a) No, it seems like the system is implemented for every employee at  $t=1$ , so the dummy could capture the effect of the new system along with the time effects going from period 0 to 1. The dummy could also capture individual effects from differences in employees.

b)  $\text{productivity} = \beta_0 + \beta_1 \text{emailsystemdummy} + \beta_2 \text{timedummy} + \epsilon_{it}$ . Since the implementation is now random, differences in employees should not affect the treatment email system coefficient. I also include a time fixed effect to control for productivity differences between the two periods.

c)  $\text{productivity} = \beta_0 + \beta_1 \text{post } t_2 + \beta_2 \text{emailsystemdummy} + \beta_3(\text{post } t_2 \times \text{emailsystemdummy}) + \epsilon_{it}$ . Having multiple time periods means we need a difference in difference estimate.

d)  $\text{productivity} = \beta_0 + \beta_1 \text{post } t_1 + \beta_2 \text{emailsystemdummy} + \beta_3(\text{post } t_1 \times \text{emailsystemdummy}) + \epsilon_{it}$ . Same model as above but our post time dummy is for  $t=1$  and beyond, our only preperiod is

t=0.

12.

a) Not consistent and not good. The estimator cannot be calculated due to x1 and x2 being perfectly collinear.

b) Yes this estimate is consistent as the OLS estimates the two parameters of the true model. However the b1 estimate may not be good, as the true model contains some fixed effect alpha which the OLS estimate is not accounting for.

c) Yes the estimate will still be consistent, since the data is randomly missing (would be different if the missing data was due to some variable). The estimate is probably not good, especially if the sample size is small.

d) Not consistent and not good, omitting a time trend if x1 is dependant on time will lead to a biased and inconsistent estimator.

13.

First running a very basic difference in difference model between time and treatment gives a significant effect of the system (productivity increased by 13.96). While it is significant at 1%, the magnitude is still fairly different from the true value of 5.

. reg y time d did

Source	SS	df	MS	Number of obs	=	100,000
Model	3.9714e+11	3	1.3238e+11	F(3, 99996)	=	1.98
Residual	6.6871e+15	99,996	6.6874e+10	Prob > F	=	0.1146
				R-squared	=	0.0001
				Adj R-squared	=	0.0000
Total	6.6875e+15	99,999	6.6876e+10	Root MSE	=	2.6e+05

  

y	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
time	-99.90269	2452.314	-0.04	0.968	-4906.407	4706.602
d	4002.104	2327.214	1.72	0.085	-559.2059	8563.415
did	13.96349	3291.177	0.00	0.997	-6436.703	6464.63
_cons	140000.8	1734.048	80.74	0.000	136602	143399.5

Including time and individual fixed effects, and all of the controls gives a similar result from above, not close to 5 but significant.

HDFE Linear regression	Number of obs	=	100,000
Absorbing 2 HDFE groups	F( 11, 89980)	=	326588.20
	Prob > F	=	0.0000
	R-squared	=	1.0000
	Adj R-squared	=	1.0000
	Within R-sq.	=	0.9756
	Root MSE	=	10.1172

y	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
did	14.97564	.1287644	116.30	0.000	14.72326	15.22801
x1	1.128718	2.087621	0.54	0.589	-2.962999	5.220436
x2	-1.995548	.0038272	-521.41	0.000	-2.003049	-1.988047
x3	-4.000001	.0040188	-995.32	0.000	-4.007878	-3.992124
x4	-9.999357	.0084036	-1189.88	0.000	-10.01583	-9.982886
x5	-.393563	.3378254	-1.16	0.244	-1.055698	.2685715
x6	1.987666	.0169184	117.49	0.000	1.954506	2.020826
x7	2.000539	.0019964	1002.07	0.000	1.996626	2.004452
x8	-.0071336	.0033639	-2.12	0.034	-.0137269	-.0005404
x9	-.392338	.3375757	-1.16	0.245	-1.053983	.2693072
x10	-.7336988	.3371707	-2.18	0.030	-1.39455	-.0728476
_cons	142204.2	.0797305	1.8e+06	0.000	142204	142204.3

Looping through different tuples of controls yielded similar results, around 15 for the DiD estimate:

tuple    beta1

x3 x4 x5 x6 x7 x8 x9 x10 14.74599

x2 x4 x5 x6 x7 x8 x9 x10 14.72339

x2 x3 x5 x6 x7 x8 x9 x10 14.70789

x2 x3 x4 x6 x7 x8 x9 x10 14.97461

x2 x3 x4 x5 x7 x8 x9 x10 14.99328

x2 x3 x4 x5 x6 x8 x9 x10 14.61633

x2 x3 x4 x5 x6 x7 x9 x10 14.97681  
x2 x3 x4 x5 x6 x7 x8 x10 14.97544  
x2 x3 x4 x5 x6 x7 x8 x9 14.97473  
x1 x4 x5 x6 x7 x8 x9 x10 14.55008  
x1 x3 x5 x6 x7 x8 x9 x10 14.4832  
x1 x3 x4 x6 x7 x8 x9 x10 14.74648  
x1 x3 x4 x5 x7 x8 x9 x10 14.7653  
x1 x3 x4 x5 x6 x8 x9 x10 14.43487  
x1 x3 x4 x5 x6 x7 x9 x10 14.74693  
x1 x3 x4 x5 x6 x7 x8 x10 14.74624  
x1 x3 x4 x5 x6 x7 x8 x9 14.74603  
x1 x2 x5 x6 x7 x8 x9 x10 14.45843  
x1 x2 x4 x6 x7 x8 x9 x10 14.72436  
x1 x2 x4 x5 x7 x8 x9 x10 14.74239  
x1 x2 x4 x5 x6 x8 x9 x10 14.36459  
x1 x2 x4 x5 x6 x7 x9 x10 14.72211  
x1 x2 x4 x5 x6 x7 x8 x10 14.72393  
x1 x2 x4 x5 x6 x7 x8 x9 14.7234  
x1 x2 x3 x6 x7 x8 x9 x10 14.71016  
x1 x2 x3 x5 x7 x8 x9 x10 14.73001  
x1 x2 x3 x5 x6 x8 x9 x10 14.34343  
x1 x2 x3 x5 x6 x7 x9 x10 14.71598  
x1 x2 x3 x5 x6 x7 x8 x10 14.70917  
x1 x2 x3 x5 x6 x7 x8 x9 14.70682

x1 x2 x3 x4 x7 x8 x9 x10	14.99426
x1 x2 x3 x4 x6 x8 x9 x10	14.6161
x1 x2 x3 x4 x6 x7 x9 x10	14.97701
x1 x2 x3 x4 x6 x7 x8 x10	14.97553
x1 x2 x3 x4 x6 x7 x8 x9	14.97473
x1 x2 x3 x4 x5 x8 x9 x10	14.63331
x1 x2 x3 x4 x5 x7 x9 x10	14.99555
x1 x2 x3 x4 x5 x7 x8 x10	14.99411
x1 x2 x3 x4 x5 x7 x8 x9	14.99334
x1 x2 x3 x4 x5 x6 x9 x10	14.61962
x1 x2 x3 x4 x5 x6 x8 x10	14.61518
x1 x2 x3 x4 x5 x6 x8 x9	14.61551
x1 x2 x3 x4 x5 x6 x7 x10	14.9768
x1 x2 x3 x4 x5 x6 x7 x9	14.97601
x1 x2 x3 x4 x5 x6 x7 x8	14.97453
x2 x3 x4 x5 x6 x7 x8 x9 x10	14.97548
x1 x3 x4 x5 x6 x7 x8 x9 x10	14.74651
x1 x2 x4 x5 x6 x7 x8 x9 x10	14.72443
x1 x2 x3 x5 x6 x7 x8 x9 x10	14.71054
x1 x2 x3 x4 x6 x7 x8 x9 x10	14.97569
x1 x2 x3 x4 x5 x7 x8 x9 x10	14.99422
x1 x2 x3 x4 x5 x6 x8 x9 x10	14.6159
x1 x2 x3 x4 x5 x6 x7 x9 x10	14.97696
x1 x2 x3 x4 x5 x6 x7 x8 x10	14.97548

x1 x2 x3 x4 x5 x6 x7 x8 x9 14.97468

x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 14.97564