w241_final_project

Loading Data

Examine data

Combining the PrelimRESULTS table with the two scripts table using left join.

```
## Joining, by = "id"
## Joining, by = "id"
```

Covariate Balance

```
## # A tibble: 6 x 4
## # Groups:   treatment, phone [4]
##   treatment phone sms   count
##   <chr>     <chr> <chr> <int>
## 1 0         0     0        13
## 2 0         1     0        23
## 3 0         1     1        23
## 4 1         0     0        15
## 5 1         1     0        44
## 6 1         1     1        45
```

Note that I used carer_group_i and address_group_i to check covariate balance. I couldn't use the original variables, because the id's were interpretated as numeric. So I had to create these two binary dummy variable.

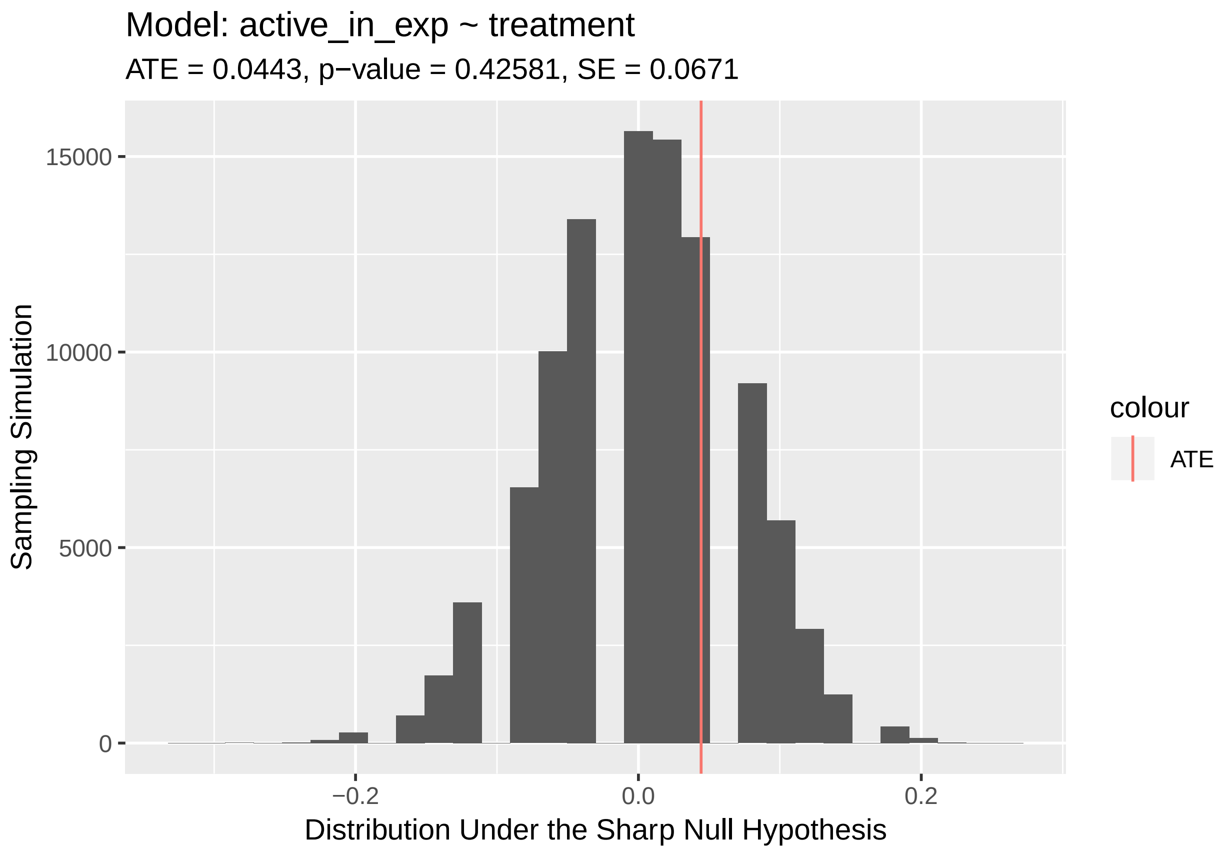
	treatment=0	treatment=1	adj.diff	adj.diff.null.sd	std.diff	z	
male	0.38	0.40	0.02	0.19	0.03	0.08	
drug_count	0.77	1.53	0.76	0.77	0.38	1.00	
active_3m	0.08	0.13	0.06	0.12	0.18	0.47	
carer_group_i	0.00	0.07	0.07	0.07	0.35	0.93	
address_group_i	0.00	0.20	0.20	0.12	0.66	1.68	.

	treatment=0	treatment=1	adj.diff	adj.diff.null.sd	std.diff	z
male	0.33	0.35	0.02	0.09	0.05	0.26
drug_count	1.78	1.91	0.13	0.37	0.06	0.34
active_3m	0.30	0.29	-0.01	0.08	-0.03	-0.15
carer_group_i	0.09	0.11	0.03	0.06	0.08	0.46
address_group_i	0.24	0.29	0.05	0.08	0.12	0.65

	sms=0	sms=1	adj.diff	adj.diff.null.sd	std.diff	z
male	0.34	0.34	-0.01	0.08	-0.01	-0.06
drug_count	1.94	1.79	-0.15	0.35	-0.07	-0.41
active_3m	0.30	0.29	-0.00	0.08	-0.01	-0.06
carer_group_i	0.12	0.09	-0.03	0.05	-0.10	-0.59
address_group_i	0.27	0.28	0.01	0.08	0.02	0.14

Hypothesis 0: treatment effect, y = active login, x = treatment

Randomization Inference: active login in exp ~ treatment, without correcting for clustered standard error



- ATE = 0.0443286
- SE = 0.0670527
- p-value = 0.42581
- The RI density plot looks so sparse is because of the low outcome, not because of small number of simulation. In fact, this is the result of 100,000 simulations.

Overall model, not splitting by 'Has Phone' vs. 'No Phone'

```
 0  1
```

0 13 15 1 46 89

- ATE is the same between RI and t-test, however, t-test uses clustered standard error.
- Treatment effect is not significant.
- Having a phone number on file is more important
- Whether the user is active during the test period is highly correlated with whether he/she was active in the app three months before the experiment.
- None of the interaction terms is significant, so no significant differential treatment effect.

Table 1: PLACE HOLDER

	active_in_exp
treatment	0.044
	(0.067)
Constant	0.186***
	(0.054)
Observations	163
R^2	0.003
Adjusted R^2	−0.004
Residual Std. Error	0.413 (df = 161)
F Statistic	0.434 (df = 1; 161)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: PLACE HOLDER

	active_in_exp
treatment	0.044
	(0.067)
Constant	0.186***
	(0.054)
Observations	163
R^2	0.003
Adjusted R^2	−0.004
Residual Std. Error	0.413 (df = 161)
F Statistic	0.434 (df = 1; 161)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: Overall Model: Treatment and Covariate Effect - NOT WEIGHTED REGRESSION

	active_in_exp	
	(1)	(2)
treatment	0.044	0.112**
	(0.067)	(0.052)
active_3m		0.641***
		(0.099)
drug_count		0.029***
		(0.009)
male		−0.005
		(0.043)
treatment:male		−0.118*
		(0.065)
treatment:active_3m		0.074
		(0.172)
treatment:drug_count		−0.034***
		(0.012)
Constant	0.186***	−0.020
	(0.030)	(0.031)
Observations	163	163
R^2	0.003	0.568
Adjusted R^2	−0.004	0.548
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4: Overall Model: Treatment and Covariate Effect, Weighted by Phone Status

	active_in_exp		
	(1)	(2)	(3)
treatment	0.030	0.027	0.111**
	(0.068)	(0.058)	(0.055)
active_3m		0.661***	0.652***
		(0.059)	(0.103)
drug_count		0.017**	0.029***
		(0.008)	(0.010)
male		−0.053	−0.005
		(0.035)	(0.045)
treatment:male			−0.115*
			(0.066)
treatment:active_3m			0.067
			(0.175)
treatment:drug_count			−0.035***
			(0.013)
Constant	0.198***	0.013	−0.020
	(0.031)	(0.049)	(0.035)
Observations	163	163	163
R^2	0.001	0.557	0.569
Adjusted R^2	−0.005	0.546	0.550
Note:	*p<0.1; **p<0.05; ***p<0.01		

Hypothesis 1: differential treatment effect by phone group, y = active login, x = treatment

Table 5: Phone Group: Treatment and Covariate Effect

	Dependent variable:				
	active_in_exp				
	(1)	(2)	(3)	(4)	(5)
treatment	0.008	−0.055	0.012	0.016	0.078
	(0.081)	(0.082)	(0.093)	(0.020)	(0.057)
drug_count		0.028***			0.033**
		(0.011)			(0.015)
treatment:drug_count		0.031			−0.037**
		(0.020)			(0.018)
sms			−0.043		−0.055
			(0.081)		(0.074)
treatment:sms			−0.007		0.007
			(0.094)		(0.068)
active_3m				0.683***	0.686***
				(0.132)	(0.125)
treatment:active_3m				0.0001	0.004
				(0.216)	(0.212)
Constant	0.239***	0.189***	0.261***	0.031***	−0.001
	(0.034)	(0.040)	(0.049)	(0.006)	(0.059)
Observations	135	135	135	135	135
R^2	0.0001	0.058	0.003	0.527	0.538
Adjusted R^2	−0.007	0.037	−0.020	0.516	0.512
Note:			*p<0.1; **p<0.05; ***p<0.01		

- Two models are specified in the table above: with phone on record vs. without phone on record.
- Model (3) In the No Phone group, there is perfect interaction between treatment assignment and active in the past 3 month. There are two people who are both in treatment and active_3m and both of them were active in during the experiment. Low sample size.
- Model (5) for the people in the control group, having received text message is likely to decrease the chance of active_in_exp. Also, one person churned. Among the people in the treatment group, receiving a SMS reduces the chance of active_in_exp by -0.01 - 0.041= -0.051. Among the people who received SMS, the treatment effect is about 0.045 - 0.041 = 0.004.

APPENDIX

Hypothesis 2: treatment effect on scripts ordered, y = scripts ordered, x = treatment

- Highly skeweed distribution, normality assumption probably won't hold given the sample size

Randomization Inference: total meds ordered in exp ~ treatment, without correcting for clustered standard error

- ATE = 0.0443286
- SE = 0.0670527
- p-value = 0.42581
- model (1): for the 'No Phone' group, being in the treatment group is predictive of total meds ordered during the experiment
- model (2): power user effect - total meds ordered in the past 3 months is highly predictive of total meds ordered during the experiment
- dont know how to interpret model (3) and (4)… maybe we should take them out
- model (5) receiving a sms reminder has a negative impact on total meds ordered?