Empirical Project 1

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Load Library and Data

```
library(pacman)
p_load(tidyverse, stargazer, data.table, tidyfast, dtplyr, haven, modelsummary,collapse)

ohp = read_dta("ohp.dta")
ohp[] = lapply(ohp, as.numeric)
ohp_dt <- as.data.table(ohp)</pre>
```

Questions

Q1

Explain the difference between the variables treatment and ohp_all_ever_survey. Explain why treatment is the treatment variable (Di), rather than ohp_all_ever_survey.

Treatment is when someone either won the OHP lottery or did not win the lottery (1, 0). ohp_all_ever_survey is if the person was every enrolled into medicaid.

Treatment is the variable we want because we are looking to see if increased access to medicaid improves health outcomes. ohp_all_ever_survey is independent of the research question and gives us a look at the compliance rate.

Q2

Provide evidence that the OHP lottery really did randomly assign individuals to treatment and control groups. Similar to Table 1 in Taubman et al. (2014), please create a nicely formatted table that reports means of 4 to 6 relevant characteristics for individuals in the control group

```
ohp_cntrl <- subset(ohp_dt, treatment ==0, select =
c(age_inp, race_black_inp, race_white_inp, race_nwother_inp, gender_inp, edu_inp))
summary(ohp_cntrl)</pre>
```

```
age_inp
                race_black_inp
                                   race_white_inp
                                                     race_nwother_inp
       :19.00
                        :0.0000
                                          :0.0000
Min.
                Min.
                                  Min.
                                                     Min.
                                                            :0.0000
1st Qu.:30.00
                 1st Qu.:0.0000
                                   1st Qu.:0.0000
                                                     1st Qu.:0.0000
Median :41.00
                Median :0.0000
                                  Median :1.0000
                                                     Median :0.0000
       :40.61
                        :0.1073
                                          :0.6898
Mean
                Mean
                                   Mean
                                                     Mean
                                                            :0.1425
3rd Qu.:50.00
                 3rd Qu.:0.0000
                                   3rd Qu.:1.0000
                                                     3rd Qu.:0.0000
Max.
       :68.00
                Max.
                        :1.0000
                                   Max.
                                          :1.0000
                                                     Max.
                                                            :1.0000
NA's
       :1
                 NA's
                        :16
                                   NA's
                                          :16
                                                     NA's
                                                            :16
  gender_inp
                     edu_inp
       :0.0000
                         :1.000
Min.
                  Min.
                  1st Qu.:2.000
1st Qu.:0.0000
Median :1.0000
                  Median :2.000
                         :2.238
Mean
       :0.5688
                  Mean
3rd Qu.:1.0000
                  3rd Qu.:3.000
       :2.0000
Max.
                  Max.
                         :4.000
                  NA's
                         :3
```

Q3

For each of the variables you summarized above, calculate:

- (i) the difference between the mean in the treatment group and the mean in the control group;2
- (ii) the standard error for the difference in means.

```
age <- lm(data = ohp_dt, age_inp ~ treatment)
edu <- lm(data = ohp_dt, edu_inp ~ treatment)
black <- lm(data = ohp_dt, race_black_inp~treatment)
white <- lm(data = ohp_dt, race_white_inp~treatment)
other <- lm(data = ohp_dt, race_nwother_inp~treatment)
gen <- lm(data = ohp_dt, gender_inp ~ treatment)</pre>
msummary(list(edu, age, white, black, other, gen), stars = TRUE, title = "Balance Check")
```

Table 1: Balance Check

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	2.238***	40.606***	0.690***	0.107***	0.142***	0.569***
	(0.012)	(0.153)	(0.006)	(0.004)	(0.005)	(0.006)
treatment	0.022	0.380 +	-0.003	-0.008	0.003	-0.006
	(0.016)	(0.212)	(0.008)	(0.006)	(0.006)	(0.009)
Num.Obs.	12 218	12 228	12 190	12 190	12 190	12 229
R2	0.000	0.000	0.000	0.000	0.000	0.000
R2 Adj.	0.000	0.000	0.000	0.000	0.000	0.000
AIC	32318.9	94851.5	15836.9	5594.0	9095.8	17552.6
BIC	32341.1	94873.8	15859.1	5616.2	9118.0	17574.8
Log.Lik.	-16156.445	-47422.765	-7915.432	-2793.996	-4544.903	-8773.298
F	1.737	3.225	0.128	1.924	0.277	0.463
RMSE	0.91	11.70	0.46	0.30	0.35	0.50

⁺ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Instead of adding the coefficients and standard errors to my earlier graph, I used the model-summary package to created a better looking graph that contains all the information. The intercept is the mean of the control group for each variable.

Q4

Is the balance table consistent with individuals having been randomly assigned to treatment group and control groups? Why or why not?

I would argue that the balance table shows individuals were randomly assigned to treatment and control groups. None of the coefficients are statistically significant which would indicate one control variable was different from the control.

Q₅

Estimate the compliance rate for the OHP experiment. That is, what is the effect of being assigned to the treatment group on the probability of being enrolled in Medicaid?

```
mod1 = lm(ohp_all_ever_survey~ treatment + age_inp + edu_inp + race_black_inp + race_white
msummary(mod1, vcov = "HC1")
```

	Model 1	
(Intercept)	0.151	
	(0.018)	
treatment	0.256	
	(0.008)	
age_inp	-0.001	
	(0.000)	
$\operatorname{edu_inp}$	-0.025	
	(0.004)	
$race_black_inp$	0.085	
	(0.015)	
$race_white_inp$	0.038	
	(0.010)	
$gender_inp$	0.089	
	(0.008)	
Num.Obs.	12187	
R2	0.091	
R2 Adj.	0.091	
AIC	14197.4	
BIC	14256.6	
Log.Lik.	-7090.691	
F	221.099	
Std.Errors	HC1	

The intercept is at 15.8% and the coefficient is at 25.4%. Averaging these two numbers show the over all compliance rate of ~20.6%.

Q6

What is the intent-to-treat (ITT) effect of the OHP experiment on health outcomes? Please create a nicely formatted table that reports ITT estimates on 4 to 6 relevant health outcomes. Again, part of this question is to get you to think about which 4 to 6 variables could be used as health outcome variables.

```
models = list(
"Depression" = lm(dep_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp + r
"Diabetes" = lm(dia_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp + race
"Hypertension" = lm(hbp_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp +
"Perscription Num" = lm(rx_num_mod_inp ~ treatment + age_inp + edu_inp + race_black_inp +
)
msummary(models, stars = TRUE, title = "List of Models")
```

Q7

What is the "treatment on the treated" effect (ATET) of the OHP experiment, i.e. the effect among those who applied for Medicaid? Estimate it for every health outcome you chose in question 6 and provide some intuition for the calculation of this estimate.

Table 2: List of Models

	Depression	Diabetes	Hypertension	Perscription Num
(Intercept)	0.064***	-0.014**	-0.002	-2.224***
	(0.009)	(0.005)	(0.010)	(0.116)
treatment	0.005	0.008***	0.002	0.111*
	(0.004)	(0.002)	(0.004)	(0.050)
age_inp	0.000*	0.001***	0.002***	0.079***
	(0.000)	(0.000)	(0.000)	(0.002)
edu_inp	-0.008***	-0.002	-0.011***	-0.031
	(0.002)	(0.001)	(0.002)	(0.028)
$race_black_inp$	0.007	-0.003	0.013 +	0.704***
	(0.007)	(0.004)	(0.008)	(0.091)
race_white_inp	0.009+	-0.009**	0.002	0.735***
	(0.005)	(0.003)	(0.005)	(0.061)
$gender_inp$	0.022***	0.006**	-0.005	0.599***
	(0.004)	(0.002)	(0.004)	(0.050)
Num.Obs.	12056	12146	11907	11 876
R2	0.004	0.008	0.012	0.127
R2 Adj.	0.003	0.007	0.012	0.126
AIC	-2194.6	-15688.0	-897.0	57337.0
BIC	-2135.4	-15628.8	-838.0	57396.1
Log.Lik.	1105.287	7851.999	456.520	-28660.498
F	7.821	15.784	24.135	287.190
RMSE	0.22	0.13	0.23	2.70

⁺ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

```
atet_dep= lm(dep_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp + race_w
  atet_dia = lm(dia_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp + race_
  atet_hyp = lm(hbp_dx_post_lottery ~ treatment + age_inp + edu_inp + race_black_inp + race_
  atet_rx = lm(rx_num_mod_inp ~ treatment + age_inp + edu_inp + race_black_inp + race_white_
  models2 = list(
    "ATET Depression" = atet_dep$coefficients[2]/mod1$coefficients[2],
    "ATET Diabetes" = atet_dia$coefficients[2]/mod1$coefficients[2],
    "ATET Hypertension" = atet_hyp$coefficients[2]/mod1$coefficients[2],
    "ATET Perscription Number" = atet_rx$coefficients[2]/mod1$coefficients[2]
  models2
$`ATET Depression`
treatment
0.01955166
$`ATET Diabetes`
treatment
0.03216333
$`ATET Hypertension`
  treatment
0.008415786
$`ATET Perscription Number`
treatment
0.4327228
```

The intent to treat coefficients for depression, diabetes, hypertension, and prescription number are 0.005, 0.008, 0.002, and 0.111. I take the compliance rate of 0.25The ATET effects are 0.0195, 0.0322, 0.0084, and 0.4327.

Q8

Do you have to worry about attrition bias in analyzing this data? Explain why or why not.

I am worried about attrition bias. Since attrition bias is where individuals non-randomly break from treatment or control guidelines, my guess would be that people of certain income strata would break more than other people from a different income strata. Someone of middle class is more likely to commit attrition in the treatment group over the control group.

Q9

Suppose that you are submitting these results to a general interest journal such as Science for publication. Write an abstract of 200 or fewer words describing what you have found in your analysis of the OHP data, similar to the abstract in Taubman et al. (2014).

Public health spending is an intensely debated topic within the United States. Data from the Oregon Health Insurance experiment was gathered to see if there is a noticeable increase in health outcomes. There are varying degrees of success in improving health outcomes for those who were given access to Medicaid, but due to some missing information, attrition bias cannot be ruled out.