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Empirical Project 1 The Oregon Health Plan Experiment (OHP)

Abstract

In 2008, the Oregon Health Program (OHP) expanded service through a lottery for eligible Oregonians on the program's waitlist. In this paper, I assess effectiveness of the randomization for use in experimental analysis by testing the treatment and control group balances and evaluate additional elements of the experiment design. I also explore implications for selected health outcomes in the data collected from lottery participants in follow-up interviews eighteen months after the lottery took place. I found that the lottery process adequately performed randomization for use in a randomized controlled experiment design. I found large differences between the intent to treat effect and the average treatment on the treated, and no estimations of intent to treat effects carry statistical significance.

Research Summary

Introduction

Many genetic, lifestyle, social, and environmental elements impact human health. The topic of the benefits versus costs of healthcare is regularly in public and political discourse, but little is available by way of definitive calculations. The 2008 lottery administered in Oregon randomly awarded (OHP) access to approximately one third of the state's waitlisted Medicare applicants. The experiment awarded OHP access to a treatment group of about 30,000 individuals from about 90,000 uninsured, low-income adults age 15 and over (Finkelstein et al. 2012).

Data

The data evaluated are a randomly selected subset of data collected by the OHP experiment administrators. This data was collected via interview eighteen months after lottery assignment. The data subset evaluated below contained records for 12,229 individuals. The

control group was represented by 5,842 members while the treated group was represented by 6,387 members' records.

I limited data provided in class to the variables for each individual's coded identifier, treatment status, age, gender, education level, whether they have signed up for OHP, whether they identify as white or not, pre- and post-lottery diagnosis status for diabetes and for high blood pressure, cholesterol readings, blood pressure readings, and post-lottery diagnosis of depression (post-lottery information taken in interviews approximately eighteen months past lottery group assignment).

Evaluation

Balance Test

Balance tests performed on observable characteristics of experiment participants can give a sense of how well the randomization can be expected to distribute unobservable characteristics between the control and treatment groups. I checked for balance of age, gender, education level, representation of white vs nonwhite individuals, and rates of pre-lottery diagnosis of diabetes and of high blood pressure. These are relevant variables to check since they are easily reported and have been shown to be related to health outcomes.

Table 1 shows the difference of means for the selected demographic and baseline health metrics between people sorted to the control vs the treatment group. Graphical representations of the balance test are in the Appendix in figures 2 and 3.

Table 1: Balance Test and Standard Error (SE) for Difference of Means

Table 1: Balance Test & SE for Difference of Means

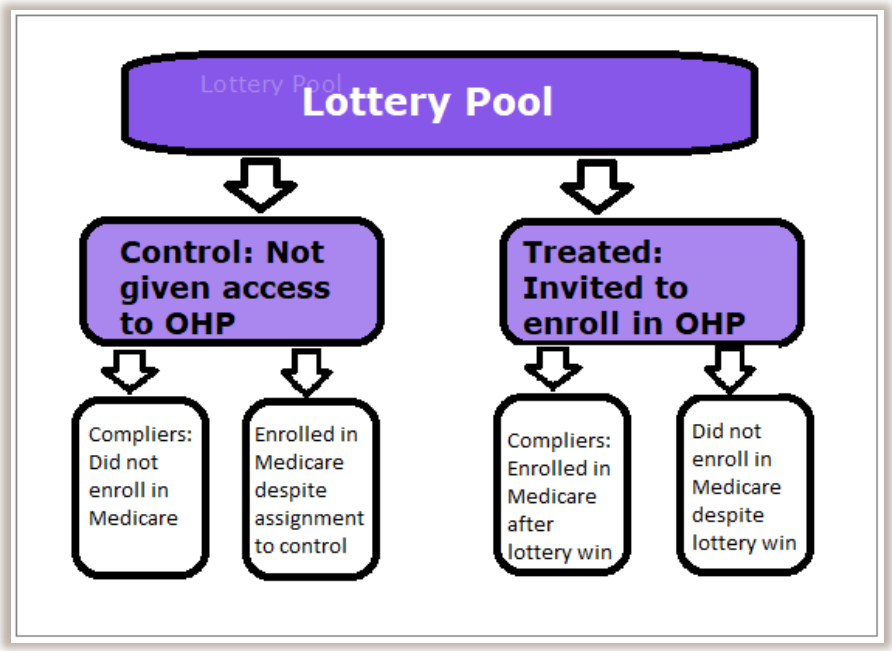
	control mean	treated diff	diff of means SE
age	40.610	0.380	0.212
	[11.685]		
non-white representation (%)	30.931	0.273	0.837
female representation (%)	56.881	-0.611	0.898
pre-lottery diabetes dx (%)	7.172	-0.080	0.466
pre-lottery high BP dx (%)	18.264	-0.134	0.699
less than hs diploma (%)	20.558	-0.173	0.731
high school diploma (%)	46.217	-1.423	0.902
post hs, no 4-yr degree (%)	22.064	1.217	0.758
4-year college degree or more (%)	11.161	0.379	0.574

Note: The treated group's difference from the control group is not statistically significant along any of the pre-treatment outcomes evaluated here.

Treatment Randomization Implications for Coping with Non-compliance and Attrition

Treatment indicates whether the person won the lottery that gave them access to healthcare. *Ohp_all_ever_survey* indicates if the individual ever signed up for Medicaid healthcare. The treatment variable is *treatment* rather than *ohp_all_ever_survey* because only access to healthcare can be randomized – the government is not forcing anyone to utilize the healthcare. Not all lottery winners (i.e., the treated) will follow through with signing up for Medicaid. Additionally, some in the control group managed to access Medicaid regardless that they did not win the lottery.

Figure 1: Lottery Mechanism and Group Types



Treatment status does not perfectly delineate individuals who received OHP because they won the lottery from those who remained uninsured. A compliance rate is calculated to bring fuller understanding to the estimations. Receiving healthcare as a result of winning the lottery is one form of compliance in this experiment. Remaining uninsured through Medicare as a result of being in the control group is another form of compliance.

The compliance rate for the OHP experiment is simply the difference between the proportion of treated individuals who complied and the proportion of untreated individuals who did not comply. This data sample shows a compliance rate just over 25%. In other words, a quarter of lottery winners enrolled in OHP *because of* their lottery win.

A careful consideration of attrition bias is also important. Experimental studies conventionally only include data on people who completed the study. Attrition, when individuals exit a study before its completion, leads to bias when it is non-random across groups. Attrition occurs for many reasons including death, adverse response to treatment, geographical move, unavailability, and refusal to continue participation. Non-randomness in the attrition is a sign to check the initial randomization.

When non-random attrition occurs, we may lose the impact of the initial randomization and render the control and treatment groups no longer comparable. The missingness of data

in the evaluated sample does not indicate non-randomness, but I recommend consulting a fuller data set for further assessment of the complete experiment.

Intent to Treat (ITT) and Average Treatment Effect on the Treated (ATET)

Two measures of the estimated effect of treatment are reported below, intent to treat (ITT) and average treatment effect on the treated (ATET). ATET describes the commonly conceptualized treatment effect, the average results for someone who fully experiences the treatment for the duration of the experiment. The OHP experiment ATET answers the question of what happens to the individuals who truly received healthcare because of the OHP lottery. ITT, by contrast, measures impacts of a treatment across the entire population that was offered treatment. It is an informative tool in evaluating a treatment because it gives an indication of the overall impact that can be expected, particularly relevant to public policy applications.

Findings & Conclusions

Through the provided data subset, I find that the OHP lottery was performed adequately as a randomization of treatment of access to enrollment in OHP, and the sample shows no sign of attrition bias. Since the randomization was properly performed, noncompliance is not a hinderance to evaluation of the data as long as a compliance rate is used to scale the estimated average treatment effects.

Estimated average ITT for selected post-lottery health outcomes are in table 2. Only one of the five estimates is statistically significant, an estimated 0.01 effect of treatment on diagnosis of depression after the lottery. This could indicate greater use of mental health services due to the treatment. The estimate is, however, quite small.

Post-lottery diagnosis rates of diabetes, high blood pressure and depression are statistically indistinguishable between control and treatment groups, as are cholesterol and blood pressure readings.

Table 2: Intent to Treat Effect Estimates (ITT) blood pressure, cholesterol, diabetes dx, high blood pressure dx, and depression dx

	bp	cholest	diabetes_dx	hbp_dx	depression_dx
(Intercept)	119.12 ***	205.76 ***	0.01 ***	0.05 ***	0.06 ***
	(0.22)	(0.45)	(0.00)	(0.00)	(0.00)
treatment	-0.06	-0.64	0.01 ***	0.00	0.00
	(0.30)	(0.61)	(0.00)	(0.00)	(0.00)

All continuous predictors are mean-centered and scaled by 1 standard deviation. Standard errors are heteroskedasticity robust. *** p < 0.001; ** p < 0.01; * p < 0.05.

Back-of-the-envelope calculation of the ATET of the OHP lottery shows many times greater average impact for those who took up Medicaid as a result of winning. Table 3 shows the estimated average treatment effect on the treated (though it does not indicate statistical significance levels). Each estimated effect of healthcare is now more than three times the size we saw when estimating an impact over the entire set of lottery winners.

Table 3: Average Treatment Effect on the Treated (ATET)

Table 3: Average Treatment Effect on the Treated

Health Outcomes	ATET
blood pressure	-0.222
cholesterol	-2.522
diabetes dx	0.034
hbp dx	1.592
depression dx	0.018

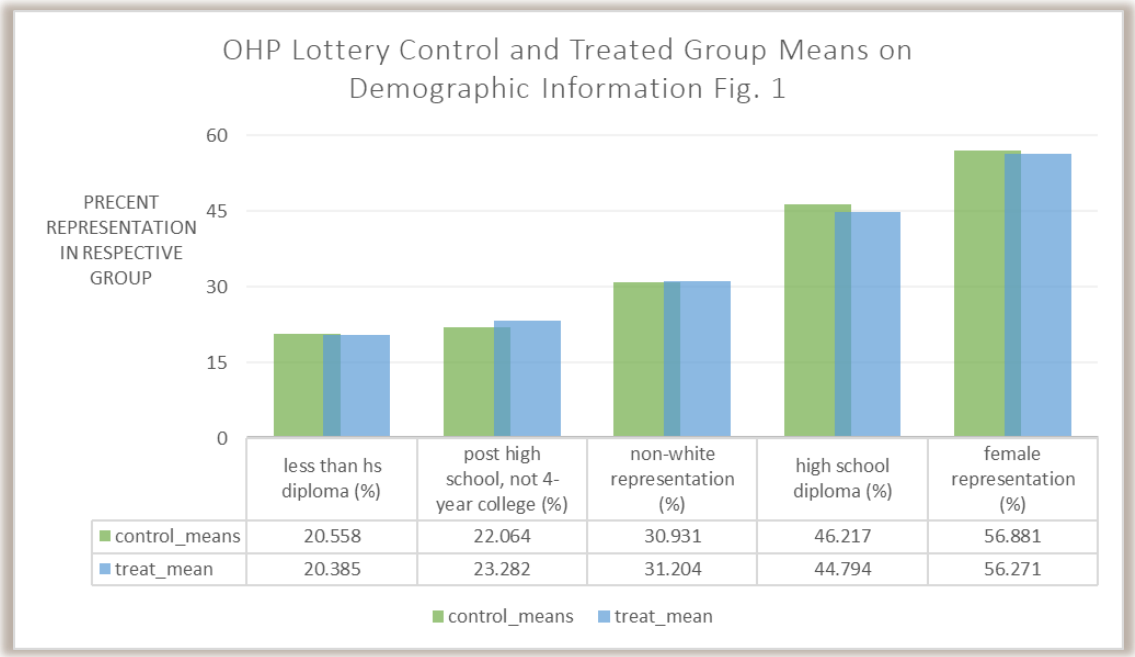
Point estimates only.

Further analysis is required to determine statistical significance of the ATET estimates.

The results of this research have not yet clarified effects of access to healthcare nor of receipt of healthcare on health outcomes. Since many elements of health change over extended periods of time, effects of healthcare access may be clearer in later periods. I suggest more in-depth analysis of subsequently gathered data from this experiment. The data processed here were gathered only about eighteen months after the lottery was administered.

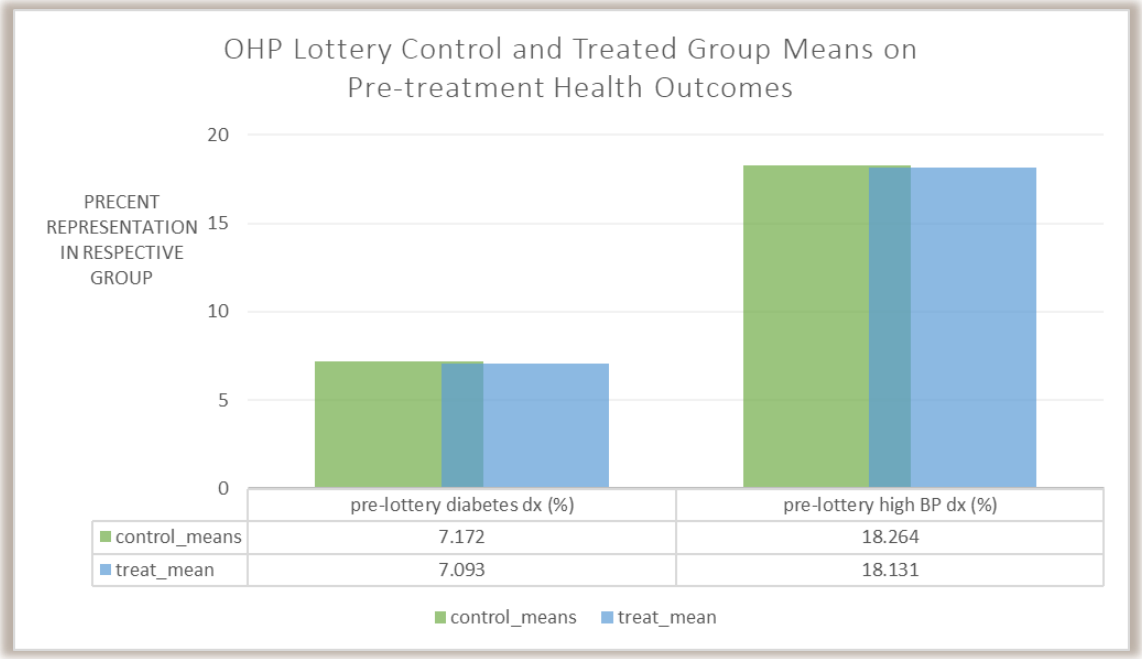
Appendix

Figure 2: OHP Lottery Balance Test on Demographics



	less than hs diploma (%)	post high school, not 4-year college (%)	non-white representation (%)	high school diploma (%)	female representation (%)
control_means	20.558	22.064	30.931	46.217	56.881
treat_mean	20.385	23.282	31.204	44.794	56.271

Figure 3: OHP Lottery Balance Test Pre-treatment Health Outcomes



	pre-lottery diabetes dx (%)	pre-lottery high BP dx (%)
control_means	7.172	18.264
treat_mean	7.093	18.131

References

Finkelstein, Amy et al. "THE OREGON HEALTH INSURANCE EXPERIMENT: EVIDENCE FROM THE FIRST YEAR." The quarterly journal of economics vol. 127,3 (2012): 1057-1106. doi:10.1093/qje/qjs020

Taubman, S. L., et al. "Medicaid Increases Emergency-Department Use: Evidence from Oregon's Health Insurance Experiment." Science, vol. 343, no. 6168, 2014, pp. 263–268., doi:10.1126/science.1246183.

Baicker, Katherine, et al. "The Oregon Experiment — Effects of Medicaid on Clinical Outcomes." New England Journal of Medicine, vol. 368, no. 18, 2013, pp. 1713–1722., doi:10.1056/nejmsa1212321.

Project .R script, Log & Output

525_Empirical_1_.R_and_output

Rebecca Amodeo

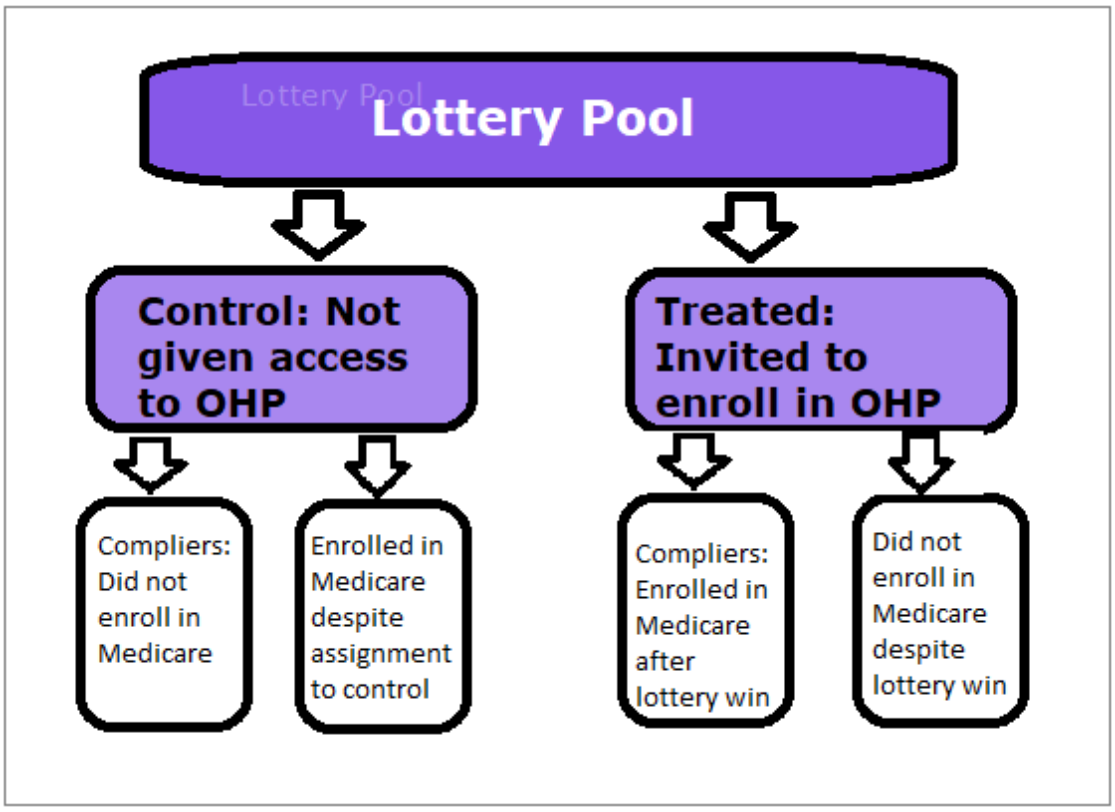


Figure 1: Lottery Mechanism and Group Types

```
install.packages("pacman")

## package 'pacman' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##  C:\Users\lanel\AppData\Local\Temp\Rtmp6xHGpB\downloaded_packages

library(pacman)
p_load(tidyverse, broom, ggplot2, foreign, skimr)
p_load(magrittr, rio, caret, finalfit, dplyr)
p_load(sandwich, lmtest, huxtable, gridExtra, jtools)
# Import Data
# convert("C:/My_Docs/525/ohp.dta", "C:/My_Docs/525/ohp.csv")
ohp = read_csv("C:/My_Docs/525/ohp.csv")

## Parsed with column specification:
## cols(
```

```
##   .default = col_double()
## )

## See spec(...) for full column specifications.

# skim(ohp)
# Balance Test
# Narrow to variables of interest
balance = c("person_id", "treatment", "ohp_all_ever_survey", "age_inp",
            "dia_dx_pre_lottery", "edu_inp", "gender_inp",
            "hbp_dx_pre_lottery", "race_white_inp", "bp_sar_inp",
            "chl_inp", "dia_dx_post_lottery",
            "dep_dx_post_lottery", "hbp_dx_post_lottery")

bal =  ohp[, (names(ohp) %in% balance)]

# Resolve NA by imputing median value
bal %<>% as.matrix() #preProcess needs matrix

bal1 = preProcess(
  x = bal,
  method = c("medianImpute")
)            %>% predict(bal) #can't forget this part!

# Subset data by treatment status
bal1 %<>% as.data.frame() #subset does not apply to matrix

control = subset(bal1, treatment == 0)
trt = subset(bal1, treatment ==1)

# Assemble balance test data
characteristics = c("age", "non-white representation (%)","female representatio
n (%)",
                    "pre-lottery diabetes dx (%)", "pre-lottery high BP dx (%)"
,
                    "less than hs diploma (%)", "high school diploma (%)",
                    "post high school, not 4-year college (%)",
                    "4-year college degree or more (%)")

# Calculate means & their differences

   # control group
age_c <- mean(control$age_inp)
age_sd <- sd(control$age_inp)
nwrep_c <- 100*(1 - mean(control$race_white_inp))
femrep <- 100*(mean(control$gender_inp))
dia_c <- 100*(mean(control$dia_dx_pre_lottery))
hbp_c <- 100*(mean(control$hbp_dx_pre_lottery))
edu1_c <- 100*(nrow(subset(control, edu_inp == 1))/nrow(control))
edu2_c <- 100*(nrow(subset(control, edu_inp == 2))/nrow(control))
edu3_c <- 100*(nrow(subset(control, edu_inp == 3))/nrow(control))
```

```
edu4_c <- 100*(nrow(subset(control, edu_inp == 4))/nrow(control))

control_means = rbind(age_c, nwrep_c, femrep,
                      dia_c, hbp_c, edu1_c, edu2_c, edu3_c, edu4_c)

   # treatment group
age_t <- mean(trt$age_inp)
nwrep_t <- 100*(1 - mean(trt$race_white_inp))
femrep_t <- 100*(mean(trt$gender_inp))
dia_t <- 100*(mean(trt$dia_dx_pre_lottery))
hbp_t <- 100*(mean(trt$hbp_dx_pre_lottery))
edu1_t <- 100*(nrow(subset(trt, edu_inp == 1))/nrow(trt))
edu2_t <- 100*(nrow(subset(trt, edu_inp == 2))/nrow(trt))
edu3_t <- 100*(nrow(subset(trt, edu_inp == 3))/nrow(trt))
edu4_t <- 100*(nrow(subset(trt, edu_inp == 4))/nrow(trt))

trt_means = rbind(age_t, nwrep_t, femrep_t,
                      dia_t, hbp_t, edu1_t, edu2_t, edu3_t, edu4_t)

    # difference of means
treated_diff = trt_means - control_means

# Calculate SE of difference in means

my_se <- function(v1, v2, n1 ,n2) {
  se.i <- sqrt((v1)/(n1) +(v2)/(n2))
  return(se.i)
}

se.age <- my_se(var(control$age_inp), var(trt$age_inp), nrow(control), nrow(trt
))
se.nwrep <- 100*(my_se(var(1 - control$race_white_inp), var(1 - trt$race_white_
inp), nrow(control), nrow(trt)))
se.femrep <- 100*(my_se(var(control$gender_inp), var(trt$gender_inp), nrow(cont
rol), nrow(trt)))
se.dia <- 100*(my_se(var(control$dia_dx_pre_lottery), var(trt$dia_dx_pre_lotter
y), nrow(control), nrow(trt)))
se.hbp <- 100*(my_se(var(control$hbp_dx_pre_lottery), var(trt$hbp_dx_pre_lotter
y), nrow(control), nrow(trt)))
se.edu1 <- 100*( my_se(var(control$edu_inp ==1), var(trt$edu_inp ==1), nrow(con
trol), nrow(trt)))
se.edu2 <- 100*(my_se(var(control$edu_inp ==2), var(trt$edu_inp ==2), nrow(cont
rol), nrow(trt)))
se.edu3 <- 100*(my_se(var(control$edu_inp ==3), var(trt$edu_inp ==3), nrow(cont
rol), nrow(trt)))
se.edu4 <- 100*(my_se(var(control$edu_inp ==4), var(trt$edu_inp ==4), nrow(cont
rol), nrow(trt)))

SE_525 = rbind(se.age, se.nwrep, se.femrep,
                                    se.dia, se.hbp, se.edu1,
```

```
                                    se.edu2, se.edu3, se.edu4)

# Q2 & Q3 Make Table_1 Data Set
BT = cbind.data.frame(characteristics, control_means, treated_diff, SE_means_di
ff = SE_525)

# write_csv(BT, "C:/My_Docs/525/BalanceTestData.csv")
```

Table 1: Balance Test & SE for Difference of Means

	control mean	treated diff	diff of means SE
age	40.610 [11.685]	0.380	0.212
non-white representation (%)	30.931	0.273	0.837
female representation (%)	56.881	-0.611	0.898
pre-lottery diabetes dx (%)	7.172	-0.080	0.466
pre-lottery high BP dx (%)	18.264	-0.134	0.699
less than hs diploma (%)	20.558	-0.173	0.731
high school diploma (%)	46.217	-1.423	0.902
post hs, no 4-yr degree (%)	22.064	1.217	0.758
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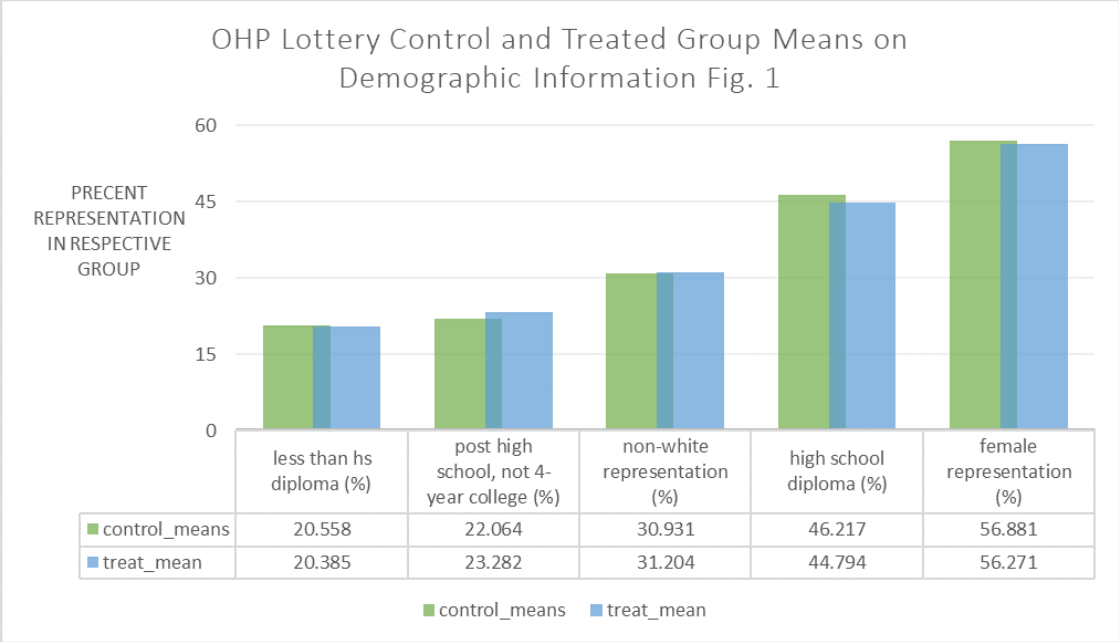
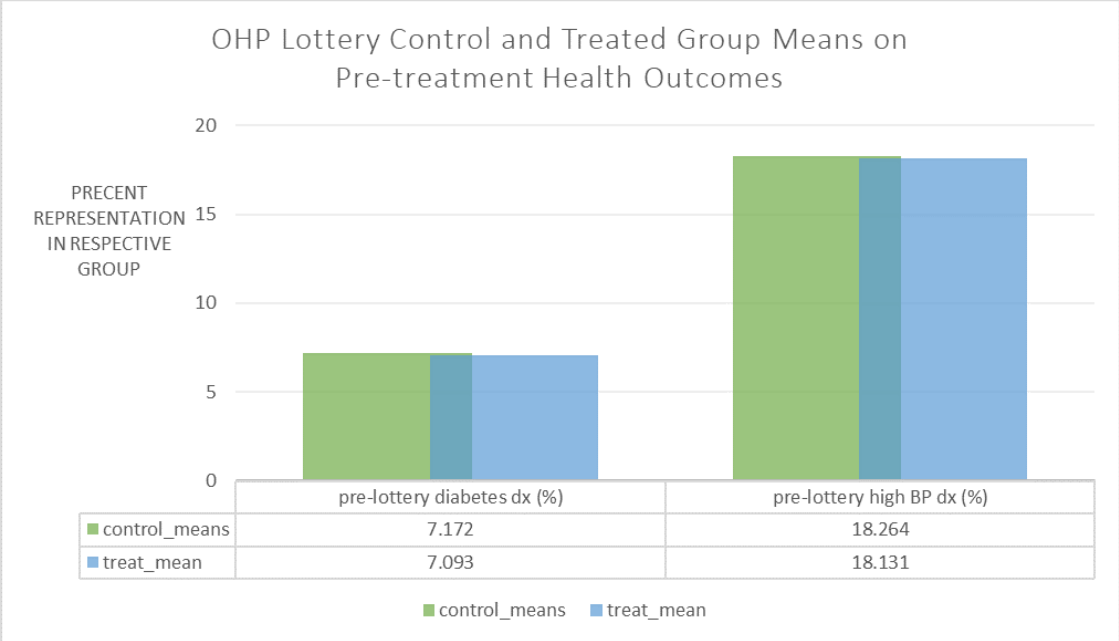
Note: The treated group's difference from the control group is not statistically significant along any of the pre-treatment outcomes evaluated here.



	less than hs diploma (%)	post high school, not 4-year college (%)	non-white representation (%)	high school diploma (%)	female representation (%)
control_means	20.558	22.064	30.931	46.217	56.881
treat_mean	20.385	23.282	31.204	44.794	56.271

Figure 2: Lottery Mechanism and Group Types



	pre-lottery diabetes dx (%)	pre-lottery high BP dx (%)
control_means	7.172	18.264
treat_mean	7.093	18.131

Figure 3: Lottery Mechanism and Group Types

```
# Q5 Compliance rate calculation
#Compliance Rate = fraction of treatment group units receiving
#treatment - fraction of control group units receiving treatment
#Multiplied by 100 to report as a %
CRate <- 100*(mean(trt$ohp_all_ever_survey) - mean(control$ohp_all_ever_survey)
)

# Health Outcomes
```

```
Y1 <- lm(bp_sar_inp~ treatment, bal1)
Y2 <- lm(chl_inp~ treatment, bal1)
Y3 <- lm(dia_dx_post_lottery~ treatment, bal1)
Y4 <- lm(dep_dx_post_lottery~ treatment, bal1)
Y5 <- lm(hbp_dx_post_lottery~ treatment, bal1)
# Q6 ITT

tabY2 <- export_summs(Y1, Y2, Y3, Y4, Y5,
  error_format = "({std.error})",
  error_pos = c("below", "right", "same"),
  ci_level = 0.95, statistics = FALSE,
  model.names = c("bp", "cholest", "diabetes_dx", "hbp_dx", "depression_dx"),
  scale = TRUE,    robust = TRUE,
  title = "Table 2: Estimated Average Treatment Effect on Health Outcomes",
  to.file = "html",  file.name = "C:/My_Docs/525/Table_2_empirical_1.html"
)

## Warning in (function (..., error_format = "({std.error})", error_style = c("
stderr", : Unrecognized statistics: FALSE
## Try setting `statistics` explicitly in the call to `huxreg()`

ITT = tabY2[4 , 2:6]
ITT = substr(ITT, start = 1, stop = 7)

ITT %<>% as.numeric()
ATET = as.data.frame(100*(ITT/CRate))
Health_Outcomes = c("blood pressure", "cholesterol", "diabetes dx", "hbp dx", "
depression dx")
atet = cbind(Health_Outcomes, ATET)

# write_csv(atet, "C:/My_Docs/525/Table_3_empirical_1.csv")
```

Table 3: Average Treatment Effect on the Treated

Health Outcomes	ATET
blood pressure	-0.222
cholesterol	-2.522
diabetes dx	0.034
hbp dx	1.592
depression dx	0.018

Point estimates only.