lab3_2024_v5

February 14, 2024

1 Lab 3: The Moving to Opportunity (MTO) Experiment

1.1 Methods/concepts: treatment effect estimation, non-compliance, intent-to-treat (ITT) effects, treatment-on-the-treated (TOT) effects, bar graphs to visualize treatment effects

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LAB DESCRIPTION

This lab uses data from the Moving to Opportunity (MTO) Experiment called **mto.dta** to estimate the causal effect of neighborhoods on mental health.[1] For more details on the variables included in these data, see Table 1. A list and description of each of the R commands needed for this lab are contained in Table 2. You should have these commands next to you as you work through the lab.

The Moving to Opportunity (MTO) Experiment was implemented by the Department of Housing and Urban Development in 1994-1998. Figure 1 shows the most common housing locations for families in the control group (the Martin Luther King Jr. Towers in Harlem) and the experimental group (Wakefield in the Bronx). Figure 2 shows the recruitment flyer for the experiment.

In today's lab, we will look at the long-run impacts on mental health of individuals who were adults when experiment was conducted in 1994-1998. We will focus on individuals in the Experimental Voucher and Control group only. The outcome variable that we will focus on is the Kessler 6 Psychological Distress Index score measured in interviews conducted between June 2008 and April 2010. The Kessler 6 Psychological Distress Index was developed by Ronald Kessler at Harvard Medical School. (Kessler was a co-author with Ludwig, Duncan, Gennetian, Katz, Kling, and Sanbonmatsu on a long-run follow up of MTO published in *Science* in 2012. The data for this lab are from their paper).

1.2 QUESTIONS

1. Briefly summarize the results from the lecture on the Moving to Opportunity Experiment. What were the results for individuals who were young children in 1994-1998? What were the results for older children and adults in 1994-1998?

[1]:
```
# QUESTION 1 Code
```

Question 1 Answer The Moving to Opportunity (MTO) experiment results indicate that for young children (those below age 13 in 1994-1998), there was a statistically significant improvement in health outcomes. However, for older children and adults from the same time period, the experiment did not have a statistically significant impact.

2. Now turn to the **mto.dta** file. What fraction of individuals in the control group moved? Report the mean of *moved* for observations with *voucher* equal to 0.

[2]:
```
#clear the workspace
rm(list=ls()) # removes all objects from the environment

#Install and load haven package
if (!require(haven)) install.packages("haven"); library(haven)

#Load stata data set
download.file("https://raw.githubusercontent.com/ekassos/ec50_s24/main/mto.
↪dta", "mto.dta", mode = "wb")
mto <- read_dta("mto.dta")

# QUESTION 2 Code
mean_moved_control <- mean(mto$moved[mto$voucher == 0], na.rm = TRUE) #Mean of␣
↪variable moved when voucher is zero
mean_moved_control
```

```
Loading required package: haven
```

0

Question 2 Answer

The mean of moved for observations with voucher equal to 0 is 0. In other words, no one from the control group moved.

3. What fraction of individuals in the experimental group moved? Report the mean of *moved* for observations with *voucher* equal to 1.

[3]:
```
# QUESTION 3 Code
mean_moved_treatment <- mean(mto$moved[mto$voucher == 1], na.rm = TRUE) #Mean␣
↪of variable moved when voucher is one
mean_moved_treatment
```

0.430631868131868

Question 3 Answer

The mean of moved for observations with voucher equal to 1 is 0.43. In other words, 43% of the treatment group moved.

4. What do your results in the previous questions tell us about the *compliance rate* in the Moving to Opportunity Experiment? Is there non-compliance, and if so, is it one-sided or two-sided?

[4]:
```
# QUESTION 4 Code
```

Question 4 Answer

Based on the previous results, where 0% of the control group moved and 43% of the treatment group moved, we can infer the following about compliance:

- The control group had perfect compliance since none of the individuals moved, which aligns with them not being offered vouchers.
- The treatment group had partial compliance since only 43% of the individuals moved, despite being offered vouchers.

This indicates that there is non-compliance in the treatment group. The non-compliance is one-sided because it only affects the treatment group—those offered vouchers who chose not to move. If there were individuals in the control group who also moved, then we would consider the non-compliance to be two-sided.

5. What is the sample mean of the *Kessler 6 Psychological Distress Index score* for individuals in the control group? Report the mean of *kessler* for observations with *voucher* equal to 0.

[5]:
```
# QUESTION 5 Code
mean_kessler_control <- mean(mto$kessler[mto$voucher == 0], na.rm = TRUE) #Mean
 ↪of variable Kessler when voucher is zero
mean_kessler_control
```

6.88059701492537

Question 5 Answer

The average Kessler score for the control group is 6.88 as shown above.

6. What is the sample mean of the *Kessler 6 Psychological Distress Index score* for individuals in the experimental group? Report the mean of *kessler* for observations with *voucher* equal to 1.

[6]:
```
# QUESTION 6 Code
mean_kessler_treatment <- mean(mto$kessler[mto$voucher == 1], na.rm = TRUE)
 ↪#Mean of variable Kessler when voucher is one
mean_kessler_treatment
```

6.29258241758242

Question 6 Answer

The average Kessler score for the treatment group is 6.29 as shown above.

7. Estimate a linear regression (regress in stata and lm in R) of *kessler* on an intercept and *voucher*. What is the relationship between the estimated coefficients in the regression and the means that you reported in questions 5-6?

[7]:
```r
# QUESTION 7 Code
lm1 <- lm(kessler ~ voucher, data = mto)
lm1
```

```
Call:
lm(formula = kessler ~ voucher, data = mto)

Coefficients:
(Intercept)      voucher
      6.881       -0.588
```

Question 7 Answer

This mean of the control group is the intercept in the regression, and the difference between the control and the treatment group is the coefficient of voucher in the regression. This is in line with the averages reported above, where we find that getting a voucher reduces the kessler score by 0.588 (6.88-6.29) on average, holding all else constant.

8. Use the regression output from question 7 to report the *intent-to-treat effect* of the experimental voucher on the *Kessler 6 Psychological Distress Index score.*

[8]:
```r
# QUESTION 8 Code
intent_to_treat <- unname(coef(lm1)["voucher"])
print(intent_to_treat)
```

```
[1] -0.5880146
```

Question 8 Answer

This coefficient value of -0.588 represents the ITT effect. It indicates that the receipt of a voucher is associated with a decrease of 0.588 points in the Kessler 6 score, on average, compared to those who did not receive a voucher.

9. Estimate a linear regression (regress in stata and lm in R) of *moved* on an intercept and *voucher*. Use the regression output to report the *compliance rate* in the experiment. Does your estimate match the calculation from question 4?

[9]:
```r
# QUESTION 9 Code
lm2 <- lm(moved ~ voucher, data = mto)
lm2
```

```
Call:
lm(formula = moved ~ voucher, data = mto)

Coefficients:
(Intercept)      voucher
 -8.381e-17    4.306e-01
```

Question 9 Answer

The coefficient of voucher implies that getting a voucher is associated with an average increase of 0.43 in moved, holding all else equal. This is in line with the earlier question where the average moved rate for treatment group was 0.43 higher than the moved rate of the average control group.

10. Use your estimates of the compliance rate and the intent-to-treat effect in the previous questions to estimate the *treatment-on-the-treated effect* of actually using the experimental voucher to move (the variable *moved*) on the psychological distress index (the variable *kessler*). Provide some intuition for the calculation of the TOT estimate.

[10]:
```
# QUESTION 10 Code
compliance_rate <- unname(coef(lm2)[["voucher"]])
treatment_on_treated <- intent_to_treat/compliance_rate
treatment_on_treated
```

-1.36546930419672

Question 10 Answer

Given that:

- ITT effect (the coefficient for voucher) = -0.588
- Compliance rate (proportion of the treatment group that moved) = 0.43

The TOT can be estimated as:

TOT = -0.588/ 0.43 TOT= -1.367

Intuition: This calculation assumes that the observed ITT effect is diluted by the individuals who did not comply (did not move despite receiving a voucher). By dividing by the compliance rate, we are scaling up the ITT effect to estimate its full impact on those who did move. This provides a more accurate estimate of the effect of the treatment for those who actually received the treatment as intended.

11. A natural, but incorrect, way of analyzing data from an experiment with non-compliance is to compare outcomes for those who actually received the treatment and those who did not receive the treatment. Imbens and Rubin (2015) refer to this incorrect analysis as an "As-Treated" analysis. Implement this incorrect approach by calculating the difference in means of *kessler* for those who moved and those who did not move.

[11]:
```
# QUESTION 11 Code

mean_kessler_moved <- mean(mto$kessler[mto$moved == 1], na.rm = TRUE)
mean_kessler_not_moved<- mean(mto$kessler[mto$moved == 0], na.rm = TRUE)

as_treated <- mean_kessler_moved - mean_kessler_not_moved
as_treated
```

-0.526330376940133

Question 11 Answer

This calculation suggests that individuals who moved have a Kessler psychological distress score that is 0.526 points lower, on average, than those who did not move. However, this approach does not account for the random assignment of the treatment and may be biased due to non-compliance and other factors not controlled for in the experimental design.

12. Another incorrect way of analyzing data from an experiment with non-compliance is to drop observations in the treatment group that did not receive the treatment (and drop observations from the control group who actually received the treatment if there are any). Imbens and Rubin (2015) refer to this incorrect analysis as a "Per Protocol" analysis. Implement this incorrect approach by calculating the differences in means for *kessler* in the experimental treatment versus control group, after excluding observations in the treatment group that did not move (i.e., voucher == 1 & moved == 0).

[12]:
```
# QUESTION 12 Code
mto_subset <- mto[(mto$voucher == 0) | ((mto$voucher == 1) & (mto$moved == 1)),␣
↪]
mean_kessler_treatment_pp <- mean(mto_subset$kessler[mto_subset$voucher == 1],␣
↪na.rm = TRUE)
mean_kessler_control_pp <- mean(mto_subset$kessler[mto_subset$voucher == 0], na.
↪rm = TRUE)
per_protocol <- mean_kessler_treatment_pp - mean_kessler_control_pp
per_protocol
```

-0.729081863410221

Question 12 Answer

This calculation suggests that, within this subset of the data, the experimental treatment group (those who received the voucher and moved) has a kessler psychological distress score that is 0.729 points lower, on average, than the control group (those who did not receive the voucher). This method, however, may introduce bias since it only considers those who complied with the treatment protocol, potentially ignoring the random assignment's intention to compare all individuals irrespective of compliance.

13. Contrast your (incorrect) "per protocol" and "as treated" estimates with the (correct) *treatment-on-the-treated effect* estimate you calculated earlier. Which method yields the biggest estimate?

[13]:
```
# QUESTION 13 Code
results_table <- data.frame(
  as_treated = as_treated,
  per_protocol = per_protocol,
  treatment_on_treated = treatment_on_treated
)

results_table <- t(results_table)
rownames(results_table) <- c('As Treated', 'Per Protocol', 'Treatment on␣
↪Treated')
```

```r
print(results_table)
```

```
                             [,1]
As Treated             -0.5263304
Per Protocol           -0.7290819
Treatment on Treated -1.3654693
```

Question 13 Answer

As seen in the table here, the treatment on treated metric is the highest (in magnitude) or implies the most decrease in the kessler score as a result of the MTO experiment.

14. Explain why the "per protocol" and "as treated" approaches lead to biased estimates, while the TOT leads to valid inference about the impact of MTO.

[14]:
```r
# QUESTION 14 Code
```

Question 14 Answer

The "Per Protocol" and "As Treated" approaches can lead to biased estimates because they violate the random assignment principle of experiments by only including individuals who comply with the treatment, potentially introducing self-selection bias. As a result, these methods create comparisons between groups that may differ systematically beyond the treatment itself.

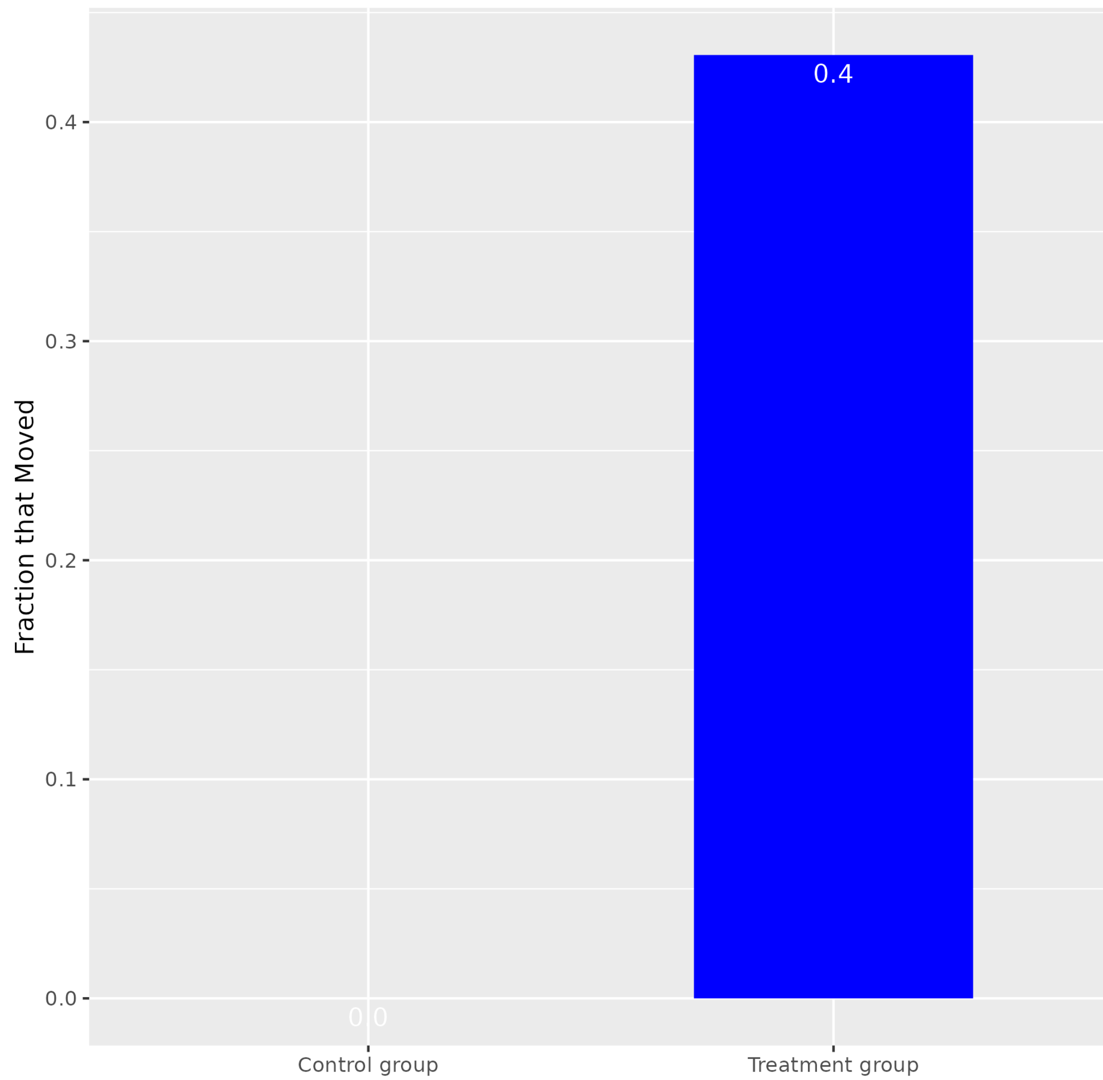
On the other hand, the Treatment-on-the-Treated (TOT) approach provides valid inference because it adjusts for non-compliance and estimates the effect of treatment among those who actually received it, preserving the benefits of randomization by accounting for the initial random assignment in its calculation.

15. The most natural way to visualize estimates from a randomized experiment is using a bar graph, with one bar representing the control group and a second bar representing the treatment group. The height of the bar for the treatment group equals the sum of the control group mean and the ITT or TOT estimate, allowing one to easily judge the magnitude of the treatment effects. Construct three bar graphs (and include them in your lab write up) to visualize:

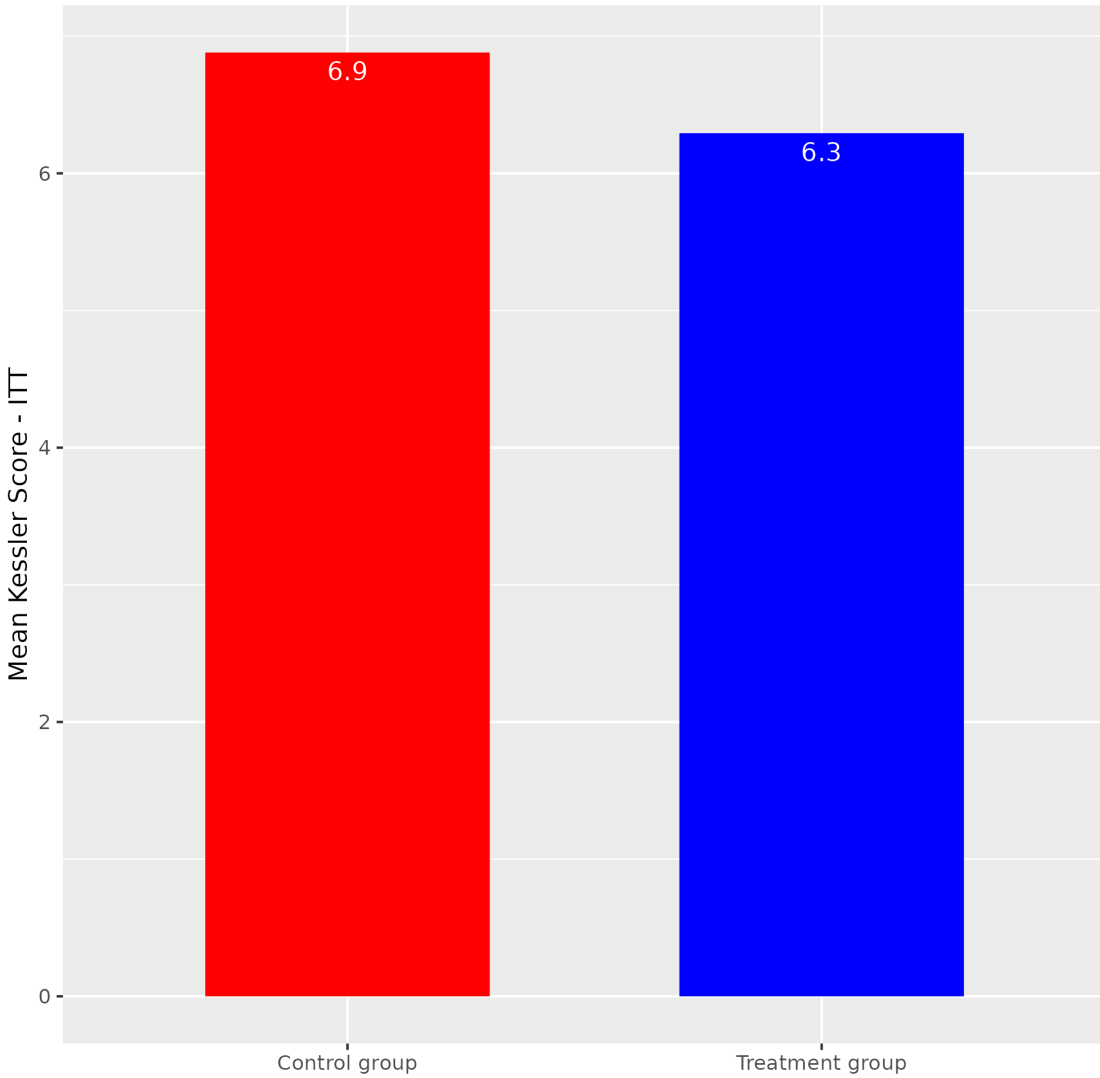
    1. The fraction of the control group that moved and the fraction of the treatment group that moved from questions 2 and 3.
    2. The mean of *kessler* in the control group and the mean of *kessler* in the treatment group, corresponding to the intent-to-treat (ITT) effect estimate from question 8.
    3. The mean of *kessler* in the control group and the *adjusted* mean of *kessler* in the treatment group, corresponding to the treatment-on-the-treated (TOT) effect from question 10.

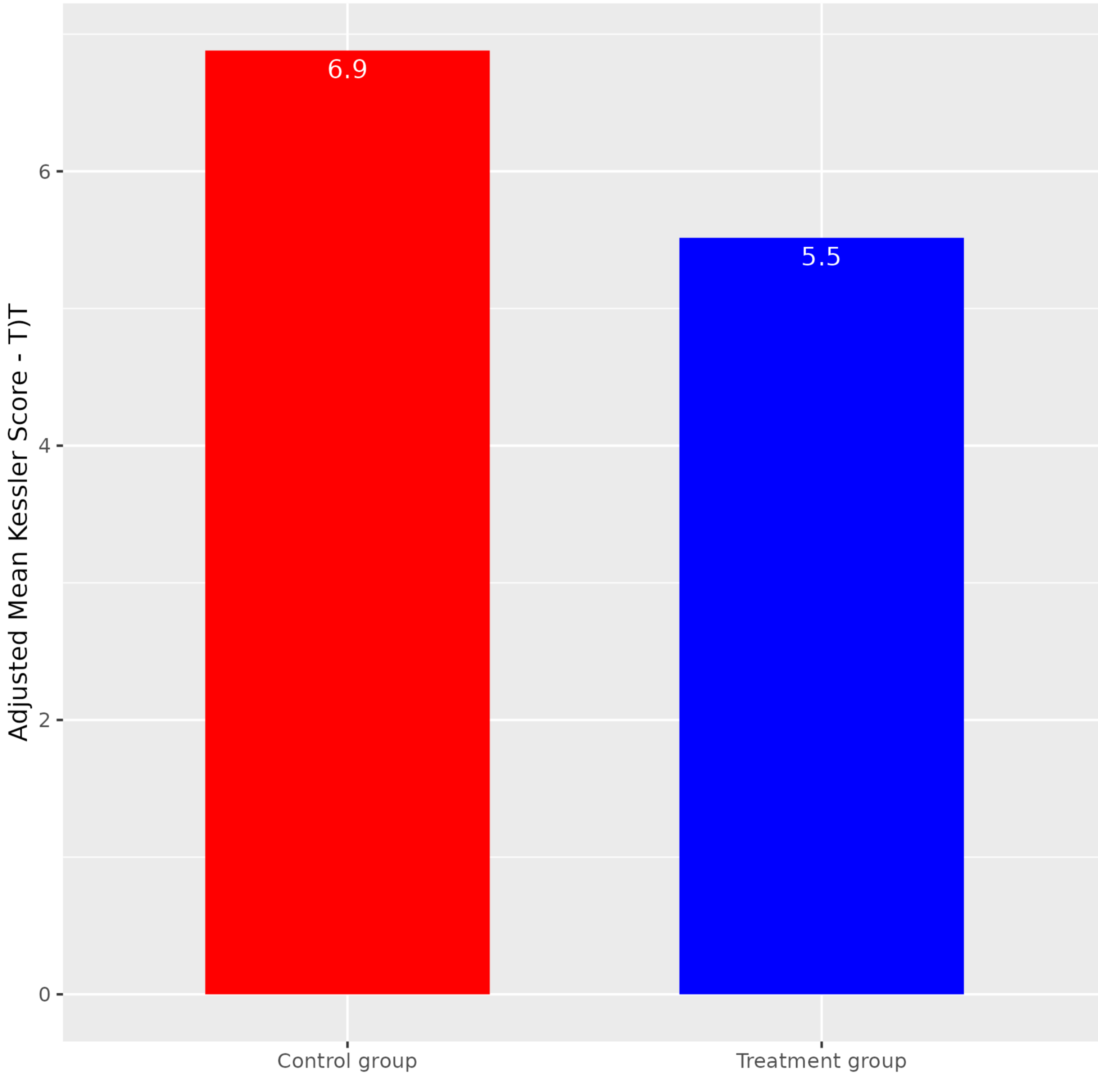
[15]:
```r
# QUESTION 15 Code
library(ggplot2)

data_for_graph1 <- data.frame(
  Moved = c(mean_moved_control, mean_moved_treatment),
  Group = c("Control group", "Treatment group")
)
```

```
data_for_graph2 <- data.frame(
  Kessler = c(mean_kessler_control, mean_kessler_control + intent_to_treat),
  Group = c("Control group", "Treatment group")
)
data_for_graph3 <- data.frame(
  Kessler = c(mean_kessler_control, mean_kessler_control + treatment_on_treated),
  Group = c("Control group", "Treatment group")
)

# ggplot(data=data_for_graph1, aes(x=Group, y=Moved, fill=Group)) +
#  geom_bar(stat="identity", show.legend = FALSE, width=.6) +
#  scale_fill_manual(values=c("red", "blue")) +
#  labs(y = "Fraction that Moved", x = "") +
#  geom_text(aes(label = sprintf("%0.1f", round(Moved, digits = 2))), vjust = 1.5, colour = "white")
# ggsave("fig1.png")

# ggplot(data=data_for_graph2, aes(x=Group, y=Kessler, fill=Group)) +
#  geom_bar(stat="identity", show.legend = FALSE, width=.6) +
#  scale_fill_manual(values=c("red", "blue")) +
#  labs(y = "Mean Kessler Score - ITT", x = "") +
#  geom_text(aes(label = sprintf("%0.1f", round(Kessler, digits = 2))), vjust = 1.5, colour = "white")
# ggsave("fig2.png")

# ggplot(data=data_for_graph3, aes(x=Group, y=Kessler, fill=Group)) +
#   geom_bar(stat="identity", show.legend = FALSE, width=.6) +
#   scale_fill_manual(values=c("red", "blue")) +
#   labs(y = "Adjusted Mean Kessler Score - T)T", x = "") +
#   geom_text(aes(label = sprintf("%0.1f", round(Kessler, digits = 2))), vjust = 1.5, colour = "white")
# ggsave("fig3.png")
```



Question 15 Answer


6.9
6.3
Mean Kessler Score - ITT
0
2
4
6
Control group
Treatment group



16. Create an annotated/commented do-file, .ipynb Python Notebook, or .R file that can replicate all your analyses above. This will be the final code that you submit on Gradescope. The motivation for using do-files and .R files is described on the next page, which has been adapted from training materials used by Innovations for Poverty Action (IPA) and the Abdul Latif Jameel Poverty Action Lab (J-PAL).

1.3 How to submit your assignment

Step 1 Access the lab assignment under the "Assignments" tab on Canvas
Step 2 Access Gradescope from Canvas
Step 3 Access the lab assignment on Gradescope
Step 4 Upload your files *Check What files to submit to confirm what files you need to submit.*

Step 5 What you'll see after submitting your lab assignment
Step 6 Check your submitted files
Step 7 You'll receive an email confirmation as well

1.4 What files to submit

If you're using Python Notebook to write your R code, and a document editor to write your answers
If you're using a Python Notebook to write your R code AND to write your answers

1.5 WHAT ARE DO-FILES AND .R FILES AND WHY DO WE NEED ONE?

Let's imagine the following situation - you just found out you have to present your results to a partner– all the averages you produced and comparisons you made. Suppose you also found out that the data you had used to produce all these results was not completely clean, and have only just fixed it. You now have incorrect numbers and need to re-do everything.

How would you go about it? Would you reproduce everything you did for Lab 1 from scratch? Can you do it? How long would it take you to do? Just re-typing all those commands into Stata or R in order and checking them would take an hour.

An important feature of any good research project is that the results should be reproducible. For Stata and R the easiest way to do this is to create a text file that lists all your commands in order, so anyone can re-run all your Stata or R work on a project anytime. Such text files that are produced within Stata or linked to Stata are called do-files, because they have an extension .do (like intro_exercise.do). Similarly, in R, these files are called .R files because they have an extension of .R. These files feed commands directly into Stata or R without you having to type or copy them into the command window.

An added bonus is that having do-files and .R files makes it very easy to fix your typos, re-order commands, and create more complicated chains of commands that wouldn't work otherwise. You can now quickly reproduce your work, correct it, adjust it, and build on it.

Finally, do-files and .R files make it possible for multiple people to work on a project, which is necessary for collaborating with others or when you hand off a project to someone else.

2 Figure 1

Most Common MTO Residential Locations in New York, NY

Note: Figure shows the most common housing locations for families in the control group (the Martin Luther King Jr. Towers in Harlem) and the experimental group (Wakefield in the Bronx) in the Moving to Opportunity Experiment.

3 Figure 2

Recruitment Flyer for the Moving to Opportunity Experiment

Note: Figure shows the recruitment flyer that was distributed in public housing units to recruit participants for the Moving to Opportunity Experiment.

3.1 DATA DESCRIPTION, FILE: mto.dta

The data consist of $N = 2,595$ individuals in the Moving to Opportunity Experiment who were adults (not children) in 1994-1998 when the randomization was conducted. (Individuals in the Section 8 group have been dropped from the data.) The Psychological Distress Index was measured in interviews conducted between June 2008 and April 2010. For more information about these data, see Jens Ludwig, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald C. Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. 2012. "Neighborhood Effects on the Long-Term Well-Being of Low-Income Adults," *Science* 331(6101): 1505-1510.

TABLE 1

Variable Definitions

Variable

Description

Obs.

Mean

St. Dev.

Min

Max

(1)

(2)

(3)

(4)

(5)

(6)

(7)

1

site

Site in 1994-1998:

2,595

3.159

1.341

1

5

1=Baltimore

2=Boston

3=Chicago

4=Los Angeles

5=New York City

2

moved

Mover/Treatment Compliance Flag:

2,595

0.242

0.428

0

1

1 = moved with experimental voucher in 1994-1998,

0 = did not move using the experimental voucher in 1994-1998

3

voucher

1 = randomly assigned to experimental voucher group in 1994-1998,

2,595

0.561

0.496

0

1

0 = randomly assigned to the control group in 1994-1998

4

kessler

Psychological Distress Index from 10-15 year follow-up interviews with families

Measured in interviews conducted between June 2008 and April 2010.

2,595

6.551

3.750

0

24

Note: Table describes variables in mto.dta.

[1] The data are a simulated dataset that preserves the key features of the Moving to Opportunity Experiment, but does not contain actual information from real households to protect their privacy.

3.2 TABLE 2: R Commands

Check the pdf and Word verisons of the assignment on Canvas.

R command

Description

```
#clear the workspace
rm(list=ls()) # removes all objects from the environment

#Install and load haven package
if (!require(haven)) install.packages("haven"); library(haven)

#Load stata data set
```

```
download.file("https://raw.githubusercontent.com/ekassos/ec50_s24/main/mto.dta", "mto.dta", mod
mto <- read_dta("mto.dta")
```

This sequence of commands shows how to open Stata datasets in R. The first block of code clears the work space. The second block of code installs and loads the “haven” package. The third block of code downloads and loads in mto.dta.

```
#Summary stats for one variable
mean(mto$yvar, na.rm=TRUE)

#Summary stats for observations with treatment_group == 1
#Subset data
new_df <- subset(mto, treatment_group == 1)

#Report mean
mean(new_df$yvar, na.rm=TRUE)

#Alternatively, do it all at once using the with() function
with(subset(mto, treatment_group == 1), mean(yvar, na.rm=TRUE))

#Summary stats for observations with treatment_group == 0
with(subset(mto, treatment_group == 0), mean(yvar, na.rm=TRUE))

#Alternatively, get both means using tapply()
tapply(mto$yvar, mto$treatment_group, mean)

#Alternatively, get both means using by()
by(mto$yvar, list(mto$treatment_group), mean)
```

We used these commands in Lab 1. These commands report means for yvar. The first line calculates these statistics across the full sample.

The other lines illustrate how to calculate these statistics for observations meeting certain criteria: when another variable in the data is equal to 1, or equal to 0.

The first few examples use the subset() function to pick out only the observations in a data frame that meet certain criteria. We can combine this with the with() function. We also have seen how to use the tapply() function to report the mean of yvar grouped by another variable treatment_group. We can also use the by() function to do the same thing.

```
#Estimate linear regression
mod1 <- lm(yvar ~ treatment_group, data=mto)
mod1
```

We used these commands in Lab 2. These commands report estimated regression coefficients from a regression of yvar on an intercept and a variable treatment_group. The intercept is always included by default, which is usually what you want.

```
#Bar graph
#Load tidyverse library
if (!require(tidyverse)) install.packages("tidyverse"); library(tidyverse)
```

```
#Create a data frame with two columns
#Column 1 is the height of the two bars (in blue)
#Column 2 is the group names (in red)
df <- data.frame(c(0.1, 0.4),
              c("Control group", "Treatment group"))

# Change name of 1st column of df to "Moved"
names(df)[1] <- "Moved"

# Change name of 2nd column of df to "Group"
names(df)[2] <- "Group"

# Bar graph displaying results
ggplot(data=df, aes(x=Group, y=Moved, fill=Group)) +
  geom_bar(stat="identity", show.legend = FALSE, width=.6) +
  scale_fill_manual(values=c("red", "blue")) +
  labs(y = "Moved Using Experimental Voucher", x = "")

ggsave("fig1.png")
```

These commands show how to draw and save a bar graph. We start by loading the tidyverse package.

We will make a data frame with two observations and two columns. Column 1 is the height of the two bars (in blue font). Column 2 is the group names (in red font). For the first observation, fill in what the height should be for the control group bar: 0.1. For the second observation, we fill in what we want for the treatment group bar: 0.4.

Then we give the first column the name "Moved" and the second column the name "Group" so that we can refer to these in the ggplot command.

We use the geom_bar plot type in ggplot. The "identity" option says to plot the numbers in the data frame as is, as opposed to plotting some statistic computed for the data frame. The scale_fill_manual() code changes the color of the bars.

[ ]: