ECON 773: Assignment 1

The BLUE Team, Jeneta Ljutic (400138620), Tadhg Taylor-McGreal (400330297), Stella Till (400364649)

2026-01-12

Table of contents

Preface

Goal

The goals of this assignment are to:

- make sure your `R`, `Positron` are set up properly
- learn to install packages in `R`
- learn to edit text in `quarto`
- learn to load data in `R`
- learn to use 5 `dplyr` verbs for basic computations with data in `R`
- learn to create some visualizations using `ggplot`
- learn to render an `.qmd` to `.pdf` (via Typst)

Instructions

Before you start the assignment, make sure to install `R` and Positron. Positron comes with command-line tools for `quarto`, which in turn includes `typst`.

You will use `quarto` for generating your assignment output file. You begin with this script downloaded from A2L. Make sure that it is placed in the same folder as any data that came with it. Instructions for editing `quarto` are discussed in class, or see the Quarto website.

To submit this assignment:

- edit the `author` and `date` fields in the `YAML` (lines 1-9). Do not touch any other line in the YAML.
- complete the questions
- render to pdf
- email to TA

Some additional instructions:

1. leave all the text between `## Question` and `### Answer` unchanged and write your answers between `### Answer` and the next `## Question`
2. for each question that involves `R` code, **do not only write R code**, but add at least one sentence before the code explaining what you are going to do, and at least one line after the R code interpreting the result
3. check spelling before submissions
4. once your assignment is complete:
   - *Render* it to pdf
   - inspect the resulting `.pdf`: would you want to grade it?
   - submit

To render this document, click the *Render* button in the menu just above the top of this file. Alternatively, use the command palette. This step may fail until you install additional packages.

Job corps

Installing packages and loading data

This question will be demonstrated in class.

For this and the next few questions, we will use the data used in H3.1. To load the data, you first have to install the `R` package that accompanies the book. To install a package in `R`, which you need to do once for every `R` installation, run `install.packages(<PACKAGE_NAME>)` in your console. We will use data from the `causalweight` package. To install it, run:

```r
install.packages("causalweight")
install.packages("causalweight", repos = "https://cloud.r-project.org")
```

The `#| eval: false` switch in the options of the above code chunk ensure that the code is not run whenever you render this `.qmd` file. Once per `R` session, and once in each `.qmd` file, you need to load the functionality of installed packages that you wish to use. You can do this by `library(<PACKAGE_NAME)`. In this case:

```r
library(causalweight)
```

```
Loading required package: ranger
```

After a `library` command, the functions and data sets in a given package are available to you. To load the `JC` data from the `causalweight` package:

```r
data(JC)
```

We will explore this data set using tools from the `tidyverse` library. If that collection of packages is not yet installed, run:

```r
install.packages("tidyverse")
install.packages("gt")
```

Load all the functionality in the `tidyverse`:

```r
library(tidyverse)
```

```
── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0
──
✔ dplyr     1.1.4     ✔ readr     2.1.6
✔ forcats   1.0.1     ✔ stringr   1.6.0
✔ ggplot2   4.0.1     ✔ tibble    3.3.0
✔ lubridate 1.9.4     ✔ tidyr     1.3.2
✔ purrr     1.2.0
── Conflicts ────────────────────────────────────────── tidyverse_conflicts()
──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all
conflicts to become errors
```

```
library(gt)
```

We will discover how to use the `tidyverse` as we go. Have a look at this vignette for the ideas behind it, and at the book R4DS for a fantastic introduction to how to use it. In this assignment, we will focus on using

- `dplyr` for data manipulation, start your practice in this R4DS chapter
- `ggplot` for data visualization, see Grammar for Graphics.

We start by putting `JC` in `tibble` format, and by having a look at the top lines using `tinytable`.

```
JC <- as_tibble(JC)
JC |>
    select(1:6) |>
    head() |>
    gt()
```

assignment	female	age	white	black	hispanic
0	0	24	0	1	0
1	1	18	1	0	0
0	1	18	0	1	0
1	1	17	1	0	0
1	0	21	0	0	1
1	0	17	0	0	1

To bring up a description of the variables, ask:

```
?JC
```

Answer the following questions, using one `dplyr` verb each:

1. using `arrange`, sort the observations by age (first) and years of education at assignment (second)

2. make a new, binarized, variable `educ_high` that equals `TRUE` if the years of education at assignment is 12 or greater, and `FALSE` otherwise. Use:
   - `mutate`
   - `ifelse`
   - the pipe operator `|>` to pass `JC` to `mutate`
   - `-> JC` to overwrite the original `tibble`
3. use `select` to keep only the 5 variables: `assignment`; the weekly earnings in fourth year after assignment; the variable indicating `female`; the education variable that you just created; the variable that indicates whether education is missing at assignment. Save the result in a new tibble called `JC_short`
4. starting from `JC_short`, use `filter` to keep only the observations for which `assignment` equals 1 and save the results as `JC_short_TG`. Create an analogous `JC_short_CG`.
5. compute the mean weekly earnings in fourth year in the `JC_short_TG` tibble, and compare it to the analogous mean in `JC_short_CG`.

Interpret the final result, and compare it to the result on H, p. 21.

Answer

1. To answer this question we will use the dplyr `arrange` tool to sort the data as directed within the question.

```
JC <- JC |>
  dplyr::arrange(age, educ)
```

JC is now sorted in descending order by age and years of education at assignment. We checked this by visually inspecting the table.

2. Using ‘mutate’, we will create the new variale called “educ_high”, where we use ‘ifelse’ so that ‘educ_high’ returns TRUE if ‘educ’ >= 12 and FALSE otherwise.

```
JC |>
  dplyr::mutate(educ_high = ifelse(educ >= 12, TRUE, FALSE)) -> JC

#Check
JC |> select(educ, educ_high) |> head()
```

```
# A tibble: 6 × 2
   educ educ_high
  <dbl> <lgl>
1     0 FALSE
2     0 FALSE
3     0 FALSE
4     0 FALSE
5     0 FALSE
6     0 FALSE
```

We have overwritten the original tibble so that JC now includes this new binarized variable. We verified our new variable by only selecting a some observations of ‘educ’ and ‘educ_high’ - it checks out.

3. Using ‘select’, we will keep only the 5 variables of interest in our new table JC_short.

```
JC_short <- JC |>
  dplyr::select(assignment, earny4, female, educ_high, educmis)

#Check
JC_short |> head()
```

```
# A tibble: 6 × 5
  assignment earny4 female educ_high educmis
       <dbl>  <dbl>  <dbl> <lgl>       <dbl>
1          1  155.       0 FALSE           1
2          0   68.4      0 FALSE           1
3          1  174.       0 FALSE           1
4          0  168.       0 FALSE           1
5          0  140.       1 FALSE           1
6          1  485.       1 FALSE           1
```

We now have a new table with only these 5 variables. We’ve checked to make sure our table is accurate by printing the first 6 rows.

4. Using ‘filter’ from JC_short, we will create two separate frames, one with treatment group observations only and the other with control group observations.

```
JC_short_TG <- JC_short |>
  dplyr::filter(assignment == 1)

JC_short_CG <- JC_short |>
  dplyr::filter(assignment == 0)
```

This works and we checked by visually analyzing the data set. We now have two tables for the treated and control groups: JC_short_TG and JC_short_CG.

5. To compute the mean weekly earnings in the fourth year for both tables created in part 4 above, we will use ‘summarise’.

```
TG_mean <- JC_short_TG |>
  dplyr::summarise(mean_earny4 = mean(earny4, na.rm = TRUE))

CG_mean <- JC_short_CG |>
  dplyr::summarise(mean_earny4 = mean(earny4, na.rm = TRUE))
```

```
#Check values
TG_mean
```

```
# A tibble: 1 × 1
  mean_earny4
        <dbl>
1        214.
```

```
CG_mean
```

```
# A tibble: 1 × 1
  mean_earny4
        <dbl>
1        198.
```

```
#Compute difference
(as.numeric(TG_mean$mean_earny4) - as.numeric(CG_mean$mean_earny4))
```

```
[1] 16.05513
```

The mean weekly earnings in the treatment group is $214 USD, compared to $198 USD in the control group. Taking the difference yields a value of $16.05513, which matches exactly the ATE reported in H, p. 21. This confirms that our findings are consistent with those in the handbook and suggests that access to Job Corps increases weekly earnings in the fourth year after assignment by approximately $16 USD on average, indicating a positive earnings effect of the program. Given that in this experiment access to the Job Corps was randomized and therefore intended to be a randomized control trial, this reflects a causal effect of access to Job Corps on earnings (assuming SUTVA holds).

Piping and `group_by`

This question will be demonstrated in class.

You will practice how to use a sequence of `pipes`, use `group_by`. You continue with the `JC_short` data that we created in the previous question.

First, use `group_by` to group the observations in `JC_short` by `female`, and comment on the result.

Second, pipe the result from `group_by` into a `summarize` command to see the means for each group in one table. Interpret the result.

Third, start with a `filter` command that keeps only those with education information available, then group by `assignment`, then compute the mean of `earny4` for each group. Interpret the result.

Fourth, repeat this, grouping by `female` **and** `assignment`. Interpret your result, discussing the conditional average treatment effect (CATE) for men and for women. Compare it to the unconditional ATE. Is the unconditional ATE an average of the two CATEs? Comment on this finding.

Answer

1. Using ‘groupby’, we will group all observations in our JC_short table by ‘female’.

```
grouped_by_female <- JC_short |> dplyr::group_by(female)
(female_counts <- grouped_by_female |> dplyr::summarise(n =
dplyr::n(), .groups = "drop"))
```

```
# A tibble: 2 × 2
  female     n
   <dbl> <int>
1      0  5180
2      1  4060
```

We’ve partitioned the dataset into two groups based on gender (male and female). This does not change the values in the data but allows subsequent summary statistics or transformations to be calculated separately for males and females. We also checked the counts for men vs women in the dataset.

2. Next, we pipe the result using ‘summarize’ to caluclate the means for each variable across our partitioned sample.

```
(means_by_female <- JC_short |>
  dplyr::group_by(female) |>
  dplyr::summarise(mean_earny4 = mean(earny4, na.rm = TRUE), n =
dplyr::n(), .groups = "drop"))
```

```
# A tibble: 2 × 3
  female mean_earny4     n
```

```
   <dbl>       <dbl> <int>
1      0        236.  5180
2      1        171.  4060
```

The resulting output reports average earnings (earny4) for each gender in a single table. The average weekly earnings in the fourth year after assignment is $171 for women and $236 for men. Therefore, earnings are about $65 USD smaller for women than for men on average.

3. Next, we will filter our original JC_short table so that only those with education available are included (where educmis = 0). Restricting the sample to individuals with non-missing education information, we then compute mean earnings (earny4) separately by assignment status.

```
filtered <- JC_short |>
  dplyr::filter(educmis == 0)

(means_by_assignment_filtered <- filtered |>
  dplyr::group_by(assignment) |>
  dplyr::summarise(
    mean_earny4 = mean(earny4, na.rm = TRUE),
    n = dplyr::n(),
    .groups = "drop"
  ))
```

```
# A tibble: 2 × 3
  assignment mean_earny4     n
       <dbl>       <dbl> <int>
1          0        198.  3601
2          1        214.  5483
```

```
#Check count & percent of educmis
JC_short |>
  dplyr::summarise(
    n_educ_mis_1 = sum(educmis == 1, na.rm = TRUE),
    n_total = dplyr::n(),
    pct_educ_mis_1 = 100 * mean(educmis == 1, na.rm = TRUE)
  )
```

```
# A tibble: 1 × 3
  n_educ_mis_1 n_total pct_educ_mis_1
         <int>   <int>          <dbl>
1          156    9240           1.69
```

The results show that mean earnings continue to differ between the treatment and control groups by about $16 USD. There are only a small number of observations with education missing at assignment (we verified this, only about 1.7% missing).

4. Next, we repeat this but group by female and assignment. Perform these operations on the filtered table created in part 3.

```
#Group by female and assignment
(means_table <- filtered %>%
group_by(female, assignment) %>%
summarise(
mean_earny4 = mean(earny4, na.rm = TRUE),
.groups =
"drop"
))
```

```
# A tibble: 4 × 3
  female assignment mean_earny4
   <dbl>      <dbl>       <dbl>
1      0          0        223.
2      0          1        246.
3      1          0        160.
4      1          1        177.
```

```
#Calculate difference in means by gender
(CATEs <- means_table %>%
group_by(female) %>%
summarise(
CATE = mean_earny4[assignment == 1] -
mean_earny4[assignment == 0]
))
```

```
# A tibble: 2 × 2
  female  CATE
   <dbl> <dbl>
1      0  23.1
2      1  17.6
```

```
#Take weighted average of CATEs
#mean(CATEs$CATE)

(avg_weighted <- CATEs %>%
  left_join(
    filtered %>% count(female),
    by = "female"
  ) %>%
  summarise(ATE = weighted.mean(CATE, n)) %>%
  pull(ATE))
```

```
[1] 20.64993
```

Grouping by both gender and assignment reveals heterogeneous treatment effects, as the CATE for men is $23.1 and the CATE for women is $17.6. Therefore, the conditional average treatment effect differs between men and women, indicating that the impact of the treatment is not uniform across genders. Recall from above that the unconditional ATE is $16, which is not equal to the weighted average of the CATEs (at about $20.6). Theoretically, the unconditional ATE should be equal to the weighted average of the CATEs that reflects the relative proportions of men and women in the sample. This does not match the expected results, which indicates that further investigation is needed on the characteristics of the data.

…

Weeks worked

You may be interested in the effect of the program on variables other than earnings. This question focuses on the proportion of weeks employed in fourth year after assignment.

First, modify the code in the previous question to answer this question using the `JC` data. This question is about the ATE, so do not split out by another variable. Interpret your findings.

Second, using `group_by` and `summarise` to split out results separately by `educ_high`. Here, `educ_high` plays the role of `female` in the first two parts of the previous question.

Finally, explore whether the effect differs depending on whether individuals have at least one child at assignment. Group only by "one child" variable, do not continue to condition on education.

Answer

1. We will use the JC data to calculate the ATE for the porportion of weeks employed in the fourth year after assignment, 'pworky4'. The code below returns the average values for treatement and control as well as the ATE in a table. First, 'group_by' splits the data into groups based on the value of the assignment variable. Next, 'summarise' collapses each group into a single row by computing the average of pworky4 within each assignment group. The 'pivot_wider' step reshapes the data from a long format into a wide format, creating separate columns for each value of assignment (prefixed with "assignment_") and filling them with the corresponding group means. Finally, 'mutate' adds the ATE variable.

```r
(JC |>
  group_by(assignment) |>
  summarise(
    mean_pworky4 = mean(pworky4, na.rm = TRUE),
    .groups = "drop"
  ) |>
  (\(df) pivot_wider(
    df,
    names_from = assignment,
    values_from = mean_pworky4,
    names_prefix = "assignment_"
  ))() |>
  mutate(
    ATE = assignment_1 - assignment_0
  ))
```

```
# A tibble: 1 × 3
  assignment_0 assignment_1   ATE
         <dbl>        <dbl> <dbl>
1         58.3         61.6  3.27
```

The estimated ATE is 3.27, indicating that assignment to the Job Corps increased proportion of weeks employed in the fourth year after assignment by approximately three weeks on average, relative to the control group, a positive effect.

2. Next, we extend the analysis by estimating the ATE conditional on education group (using the 'educ_high' variable created above) to examine whether the impact of the treatment differs based on education level. The logic is very similar to the part 1, but this time we are grouping by 'educ_high' and 'assignment'.

```
(JC |>
  group_by(educ_high, assignment) |>
  summarise(
    mean_pworky4 = mean(pworky4, na.rm = TRUE),
    .groups = "drop"
  ) |>
  (\(df) pivot_wider(
    df,
    names_from = assignment,
    values_from = mean_pworky4,
    names_prefix = "assignment_"
  ))() |>
  mutate(
    CATE = assignment_1 - assignment_0
  ))
```

```
# A tibble: 2 × 4
  educ_high assignment_0 assignment_1  CATE
  <lgl>            <dbl>        <dbl> <dbl>
1 FALSE             55.8         58.7  2.91
2 TRUE              67.7         71.1  3.35
```

For individuals with 12 years of education or more ('educ_high' = TRUE), the treatment increases proportion of weeks employed in the fourth year after assignment by 3.35 weeks. For those with less than 12 years of education (educ_high = FALSE), the estimated effect is slightly smaller, at 2.91 weeks. These results suggest that access to the Job Corps has a slightly larger impact on employment for higher-educated individuals, although the difference is relatively small (0.44 weeks).

3. Using 'haschild' ('haschild' = 1 indicates at least one child, 'haschild' = 0 indicates no children at assignment), we'll explore the effect of the program conditional on whether individuals have at least one child at assignment.

```
(JC |>
  group_by(haschild, assignment) |>
  summarise(
    mean_pworky4 = mean(pworky4, na.rm = TRUE),
    .groups = "drop"
  ) |>
  (\(df) pivot_wider(
    df,
    names_from = assignment,
    values_from = mean_pworky4,
    names_prefix = "assignment_"
  ))() |>
  mutate(
    CATE = assignment_1 - assignment_0
  ))
```

```
# A tibble: 2 × 4
  haschild assignment_0 assignment_1  CATE
     <dbl>        <dbl>        <dbl> <dbl>
1        0         59.0         61.7  2.76
2        1         55.6         61.2  5.61
```

For individuals without children at assignment (‘haschild’ = 0), the estimated CATE is 2.76 weeks of employment in the fourth year, while for those with at least one child at assignment (‘haschild’ = 1), the effect is substantially larger at 5.76 weeks (for a difference of 3 weeks). These results indicate that the treatment has a stronger impact on employment for parents, suggesting that access to the Job Corps may be particularly beneficial for individuals with children.

Boxplots

This exercise will be demonstrated in class.

You will practice using ggplot to create data visualizations. Learning to work with ggplot could be its own course. In this course, it will be sufficient to modify the code discussed in class. For a deeper dive, start with these resources.

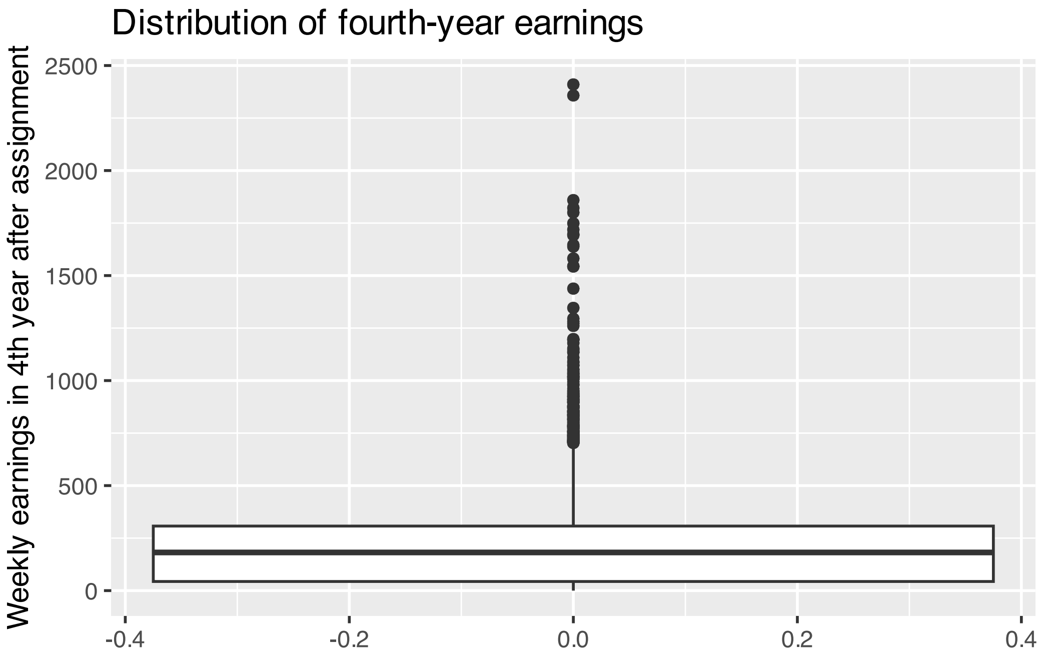
You will continue with the JC data. A useful data summary for our purpose is the boxplot.

First, make a boxplot of earny4. Second, make a boxplot of log earnings for those with positive earnings. Third, split out each of the two boxplots by assignment.

Answer

1. To code our boxplot we use ‘ggplot’. Using ‘ggplot’ allows us to build the plot step by step using JC data. Within our ‘ggplot’ bracket, we indicate that the y axis should show the category for earnings after the fourth year of the program. Following ‘ggplot’, we use ‘geom_boxplot’. This tells R to put the JC data into a boxplot. In the last step of the code, we set the titles. We repeated this code skeleton for all of the following boxplots, changing the variables to either be in logs, sorted by assignment, or both.

```r
ggplot(JC, aes(y = earny4)) +
  geom_boxplot() +
  labs(
    y = "Weekly earnings in 4th year after assignment",
    title = "Distribution of fourth-year earnings"
  )
```

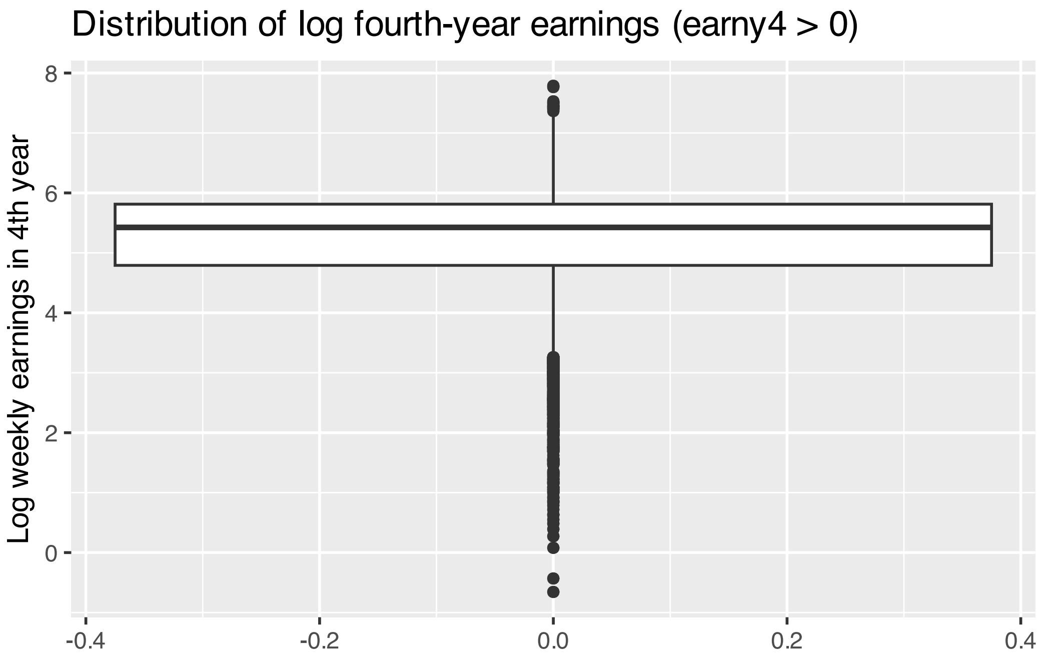


This boxplot shows the weekly earnings in the fourth year after assignment on the y-axis and in this boxplot we see a skew to the right. This indicates that most individuals earn relatively low wages. The high earning individuals appear to be outliers. This suggests that only some individuals benefit largely in the fourth year post Job Corps program which indicates that the treatment did not have the same effect across all participants.

In this plot, the effect of earnings are skewed by the extreme high values. This is because in a chart using levels, the differences are absolute and are thus highly influenced by outliers. This motivates the use of log earnings in the following charts since taking the logs compresses the upper tail of the distribution, allowing for comparisons which reflect proportional differences in earnings rather than absolute differences.

2. Next, we make a boxplot of log earnings, filtering on positive earnings. To do this, we used 'filter' to keep 'earny4'>0, this ensures that only positive values are included, essential when taking a logarithim, and then took the log of earnings.

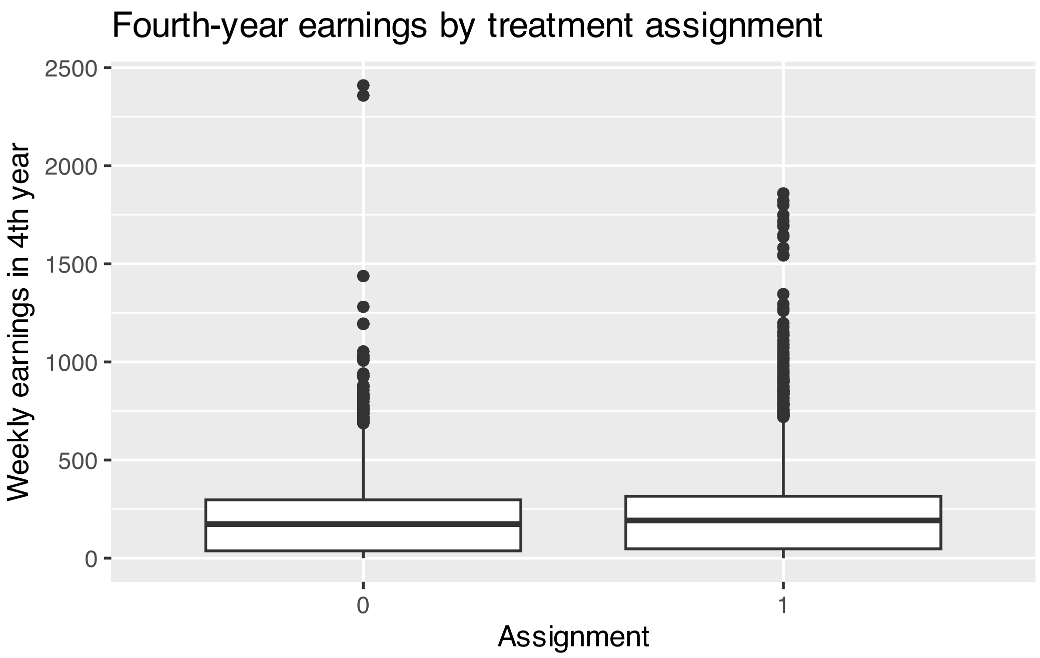
```r
ggplot(
  JC |> filter(earny4 > 0),
  aes(y = log(earny4))
) +
  geom_boxplot() +
  labs(
    y = "Log weekly earnings in 4th year",
    title = "Distribution of log fourth-year earnings (earny4 > 0)"
  )
```



The second boxplot shows the distribution of log earnings for those with positive earnings. In this plot, we see that the earnings are more centred. This indicates that once we restrict for positive earnings, measured on a log scale the upper tail on the distribution becomes compressed. There remain some lower outliers, indicating that some individuals continue to have low but positive earnings. Thus, even when separating for positive earnings, heterogeneity of the results remain suggesting that there are other characteristics that influence earnings in the period four years after the program.

3a. Lastly, we will split out the first boxplot (without the log of earnings) by assignment. To do this, we type ‘factor’(assignment, …) in the first line of ‘ggplot’ code.

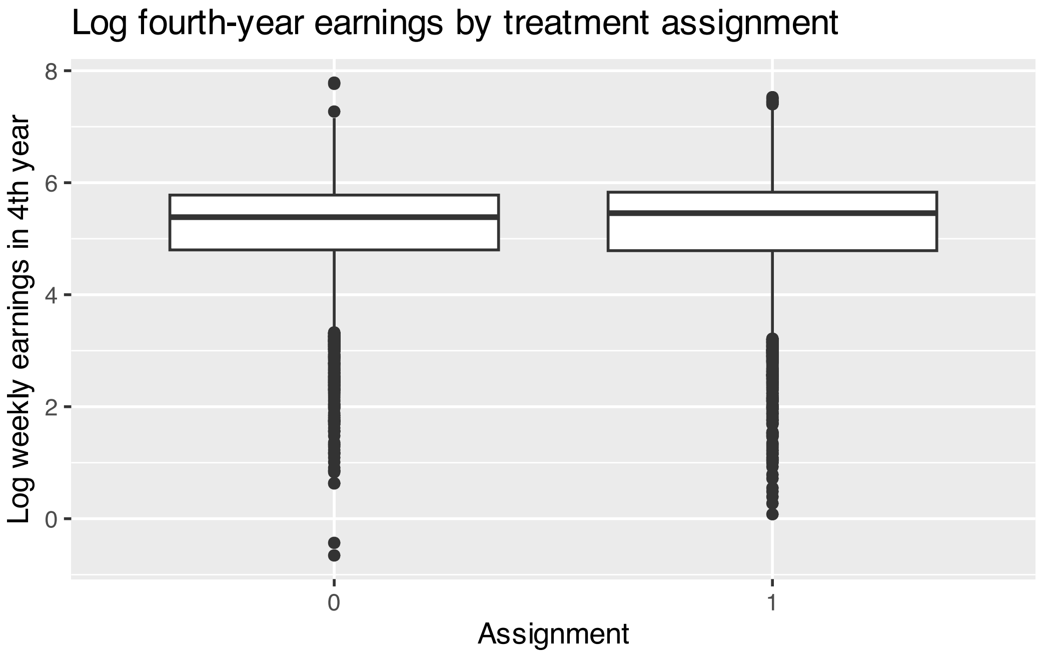
```r
ggplot(JC, aes(x = factor(assignment), y = earny4)) +
  geom_boxplot() +
  labs(
    x = "Assignment",
    y = "Weekly earnings in 4th year",
    title = "Fourth-year earnings by treatment assignment"
  )
```



The boxplot, shows the weekly earnings in the fourth year after the treatment and is grouped by assignment on the x-axis. The y-axis shows the level of weekly earnings. In this plot, all earnings are positive. Dividing the earnings distribution by assignment highlights the differences in earnings between the control group (assignment = 0) and the treatment group (assignment = 1). We see a strong right-skew of earnings in both groups. This indicates that most individuals earn relatively low wages. We can note that there are few outliers in the control group with very high earnings. The outliers in both the treatment and the control group suggest that there may be heterogeneous program effects. However, it is important to distinguish that the treatment group has shows a higher median level of earnings. This suggests that there was a positive effect from the Jobs Corps program.

3b. Lastly, we will split out the second boxplot (with log earnings) by assignment, using very similar code, but filtering and taking the log on earnings.

```r
ggplot(
  JC |> filter(earny4 > 0),
  aes(x = factor(assignment), y = log(earny4))
) +
  geom_boxplot() +
  labs(
    x = "Assignment",
    y = "Log weekly earnings in 4th year",
    title = "Log fourth-year earnings by treatment assignment"
  )
```



This final boxplot shows the positive earnings by assignment. It compares the distribution of log weekly earnings in the fourth year after the assignment between the control group (assignment = 0) and the treatment group (assignment = 1). All individuals in this plot are restricted to have positive earnings. On the boxplot, we see that there is a higher median log earnings in the treatment group. This indicates that those assigned to the Jobs Corps training program have higher typical earnings four years after the treatment assignment. This suggests a positive average treatment effect of Jobs Corps on earnings.

There is substantial overlap between the distributions of the treatment and control group. This suggests that the program's effects were moderate and there may be other characteristics driving certain individuals to earn higher wages.

…

Scatterplots

You are going to use scatterplots to visualize the relationship between pre-program earnings, post-program earnings, and treatment assignment. This question will require you to figure out how `geom_point` works. Use the sources provided in the instructions.

First, create a scatterplot with average weekly gross earnings at assignment on the horizontal axis, and weekly earnings in fourth year after assignment on the vertical axis. Use only individuals that have positive earnings at both of those moments. Use log earnings in your plot. Hint: scatter plots use `geom_point` instead of `geom_boxplot`.

Second, add a least squares fit by using `geom_smooth`.

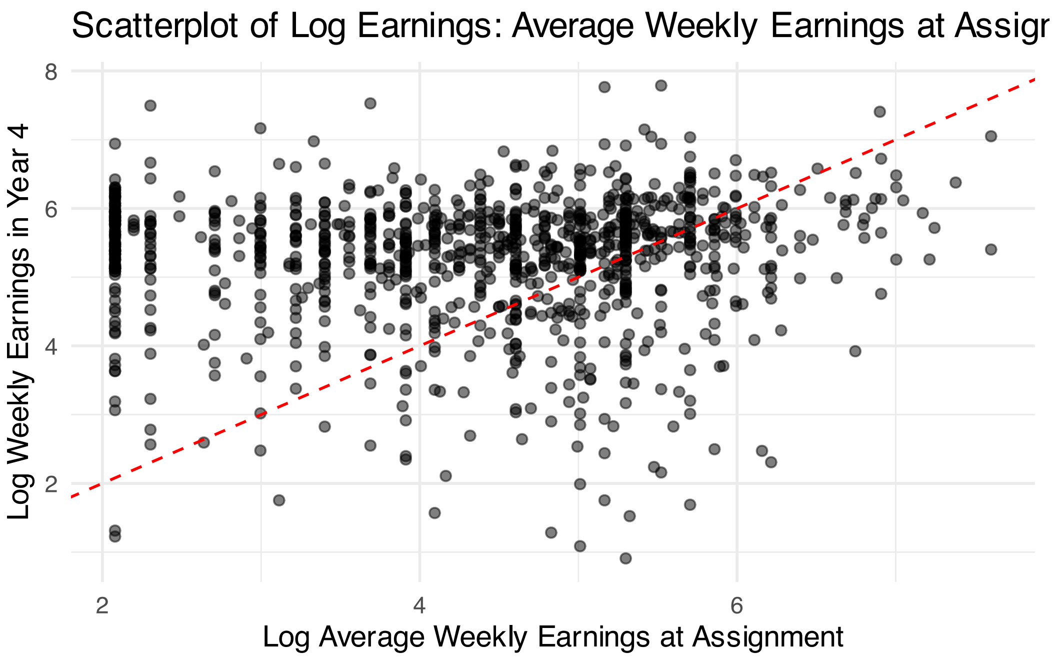
Third, split the results out by `assignment`, by setting `colour = assignment`. Interpret your findings.

Answer

1. We will use 'ggplot' and 'geom_point' to create a scatterplot of logged earnings at assignment, 'mwearn' and at year 4, 'earny4'. The code filters the data to include only individuals with positive earnings at assignment and in year 4 so that taking logarithms is valid. It creates a scatterplot of log earnings at assignment versus log earnings in year 4, adds semi-transparent points, and overlays a dashed 45-degree reference line showing where earnings would be equal in both periods.

```r
library(ggplot2)

JC |>
  filter(mwearn > 0, earny4 > 0) |>  # keep only positive earnings
  ggplot(aes(x = log(mwearn), y = log(earny4))) +
  geom_point(alpha = 0.5) +          # semi-transparent points for clarity
  geom_abline(
    slope = 1,
    intercept = 0,
    linetype = "dashed",
    color = "red"
  ) +                                # 45-degree reference line
  labs(
    x = "Log Average Weekly Earnings at Assignment",
    y = "Log Weekly Earnings in Year 4",
    title = "Scatterplot of Log Earnings: Average Weekly Earnings at
Assignment vs Year 4"
  ) +
  theme_minimal()
```

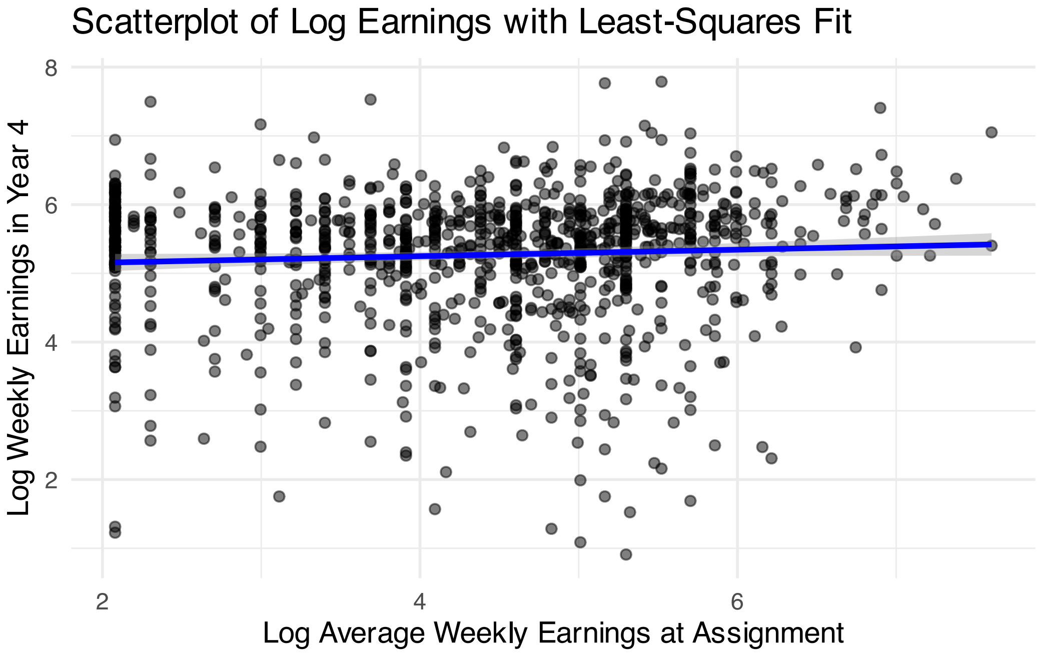


The scatterplot of log earnings at assignment versus log earnings in the fourth year shows that there is a positive correlation between log weekly earnings at assignment (x-axis) and log weekly earnings in Year 4 (y-axis). Generally, as initial earnings increase, earnings four years later also tend to be higher. However, the distribution of data points is quite dispersed, suggesting that while there is a trend, initial earnings are not necessarily a perfect predictor of future earnings. Additionally, a significant portion of the data points, especially on the left side of the graph (lower initial earnings), sit well above the red line. This suggests that people starting with lower earnings saw substantial relative growth over the four-year period. As you move to the right (higher initial earnings), the data points cluster much closer to the red line, and more points begin to fall below it.

2. Next, we will use geom_smooth() to add a least-squares regression line to our scatterplot to show the overall trend in log earnings. The code is similar to above, but overlays a least-squares regression line with a confidence band using geom_smooth(method = “lm”).

```
JC |>
  filter(mwearn > 0, earny4 > 0) |>
  ggplot(aes(x = log(mwearn), y = log(earny4))) +
  geom_point(alpha = 0.5) +                       # points
  geom_smooth(
    method = "lm",
    se = TRUE,
    color = "blue"
  ) +                                             # least-squares fit with
confidence band
  labs(
    x = "Log Average Weekly Earnings at Assignment",
    y = "Log Weekly Earnings in Year 4",
    title = "Scatterplot of Log Earnings with Least-Squares Fit"
  ) +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```

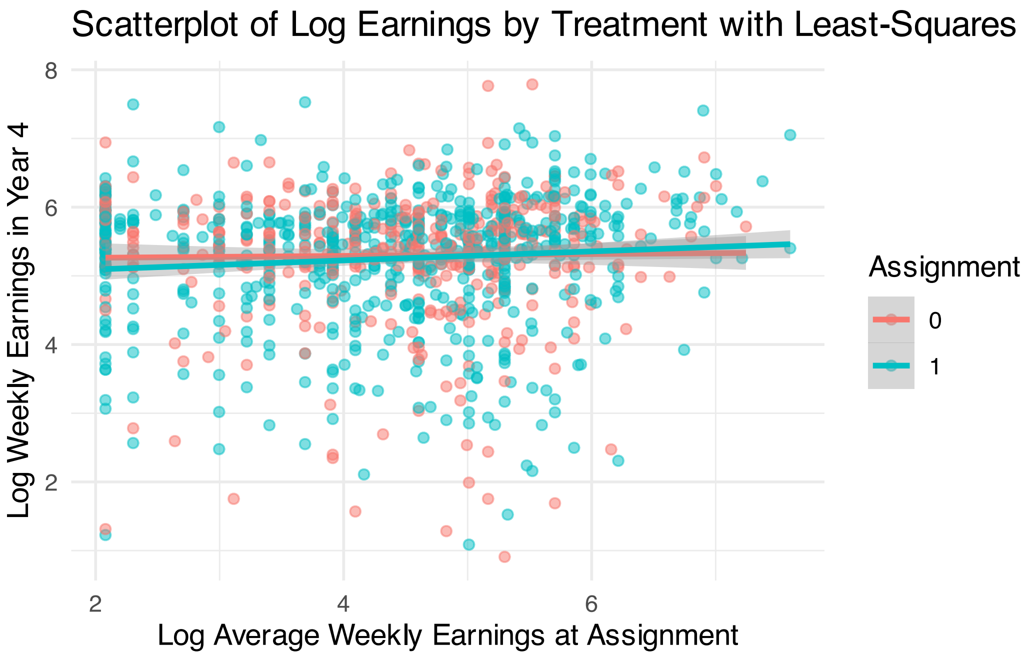


The scatterplot with a least-squares fit shows that earnings at assignment are only weakly predictive of earnings in the fourth year. The slope of the regression line is slightly upward, indicating that higher initial earnings are associated with slightly higher later earnings, but the relationship is modest. Most people, regardless of their starting point, seem to converge toward a similar average log earnings (around 5.5) in Year 4, and there is considerable variation in earnings growth across individuals. Therefore, since the slope is so low, knowing someone's starting log earnings doesn't help much in predicting their future log earnings in this specific context. The thin grey band surrounding the blue line is the confidence interval. Because this band is very narrow, we can be statistically confident that the "true" relationship is indeed this flat.

3. Lastly, we will add colour by treatment group to see separate trends for treated and control groups and their fitted lines. This is again similar to the code above, but adds colours to points by treatment group ('assignment') using 'factor' to treat assignment as a categorical variable rather than a numeric one. This ensures that each group gets a separate colour and that geom_smooth() draws separate regression lines with confidence bands for each group.

```
JC |>
  filter(mwearn > 0, earny4 > 0) |>
  ggplot(aes(x = log(mwearn), y = log(earny4), color = factor(assignment))) +
  geom_point(alpha = 0.5) +                         # semi-transparent points
  geom_smooth(method = "lm", se = TRUE) +        # separate regression lines by
color with confidence bands
  labs(
    x = "Log Average Weekly Earnings at Assignment",
    y = "Log Weekly Earnings in Year 4",
    color = "Assignment",
    title = "Scatterplot of Log Earnings by Treatment with Least-Squares Fit"
  ) +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```



The control group's line (denoted in orange) and the treated group's line (denoted in blue) both have very shallow, slightly positive slopes (although the treatment line is slightly steeper), which indicates that while initial earnings have a positive relationship with future earnings, the effect is relatively weak. Both regression lines are nearly identical and sit almost on top of one another. This suggests that access to the Job Corps did not significantly change the outcome of weekly earnings in Year 4 compared to the control group. Additionally, since the shaded areas (representing the confidence intervals) overlap almost entirely across the whole horizontal axis, this suggests that there is no statistically significant difference between the two groups' earnings outcomes, however a formal test would be needed to conclude.

HIV information experiment

Loading data

From the `causaldata` package, load the `thornton_hiv` data, and then turn it into a tibble after removing all missing data using `drop_na`. You can use `?thornton_hiv` to find the variable descriptions. This exercise is based on the replication in The Mixtape, Chapter 4.

You can read Chapter 4 as a secondary source about the material we discussed this week. Please read Section 4.1.5 before attempting this exercise, to read the necessary background about this experiment. Reading this section is also part of your self-study about SUTVA.

> Respondents in rural Malawi were offered a free door-to-door HIV test and randomly assigned no voucher or vouchers ranging from $1–$3. These vouchers were redeemable once they visited a nearby voluntary counseling and testing center (VCT).

In this data set, which variable corresponds to D? Which variable corresponds to Y?

First, use `group_by` and `summarize` to compute the group-specific means. Friendly reminder to use `drop_na()`! Second, repeat this exercise to compute a group-specific mean for each value of `tinc`. Third, take the resulting table and plot it using `geom_point` and/or `geom_line`. Interpret the results.

Answer

In the potential outcomes framework: - Y (outcome) is got: an indicator for whether the respondent collected their HIV test results. - D (treatment) can be defined as: * any: a binary indicator for receiving any voucher * tinc: the dollar value of the voucher (0–3 USD)

Because assignment is randomized, differences in mean outcomes across treatment groups can be interpreted causally, subject to SUTVA.

```r
install.packages("causaldata")
```

```r
# Packages
library(causaldata)
library(dplyr)
library(tidyr)
library(ggplot2)
library(tibble)
data("thornton_hiv")
thornton <- thornton_hiv |>
drop_na() |>
as_tibble()
```

Remove missing observations and convert to tibble

We next compute group-specific means of the outcome got by the binary treatment indicator any. This estimates the intent-to-treat (ITT) effect of being offered any voucher.

```
by_any <- thornton |>
group_by(any) |>
summarize(
mean_got = mean(got),
n = n(),
.groups = "drop"
)
```

Display the group means

```
by_any
```

```
# A tibble: 2 × 3
    any mean_got     n
  <dbl>    <dbl> <int>
1     0    0.340   621
2     1    0.791  2204
```

The table reports mean HIV testing uptake (got) by voucher assignment (any).

The difference in means is: 0.791 − 0.340 = 0.451

Interpretation: Being offered any voucher increases the probability of HIV testing by approximately 45.1 percentage points. Because voucher assignment was randomized, this difference is the intent-to-treat (ITT) effect of financial incentives on testing uptake.

Mean outcomes by voucher amount (dose-response)

We now compute group-specific mean outcomes for each voucher amount (tinc). This allows us to assess whether testing uptake increases with the size of the incentive.

```
by_amount <- thornton |>
group_by(tinc) |>
summarize(
mean_got = mean(got),
n = n(),
.groups = "drop"
)
```

```
by_amount
```

```
# A tibble: 27 × 3
     tinc mean_got     n
    <dbl>    <dbl> <int>
 1 0         0.340   621
 2 0.0946    0.632    57
 3 0.189     0.647   153
 4 0.284     0.654    81
 5 0.378     0.698    63
 6 0.473     0.714   203
 7 0.567     0.784    37
 8 0.662     0.725    40
 9 0.756     0.857     7
10 0.851     0.75      8
# ℹ 17 more rows
```

Interpretation of dose–response results

The table reports mean HIV testing uptake by the dollar value of the voucher.

Baseline (tinc = 0): - Mean uptake = 0.340 (34.0%) - This is the control group with no financial incentive.

Low incentive range (approximately $0.10 – $0.30): - Mean uptake rises sharply to about 0.63–0.65.

Moderate incentive range (approximately $0.38 – $0.57): - Mean uptake increases further, reaching roughly 0.70–0.78. - The increase remains positive but is smaller than the jump from zero to very small incentives.

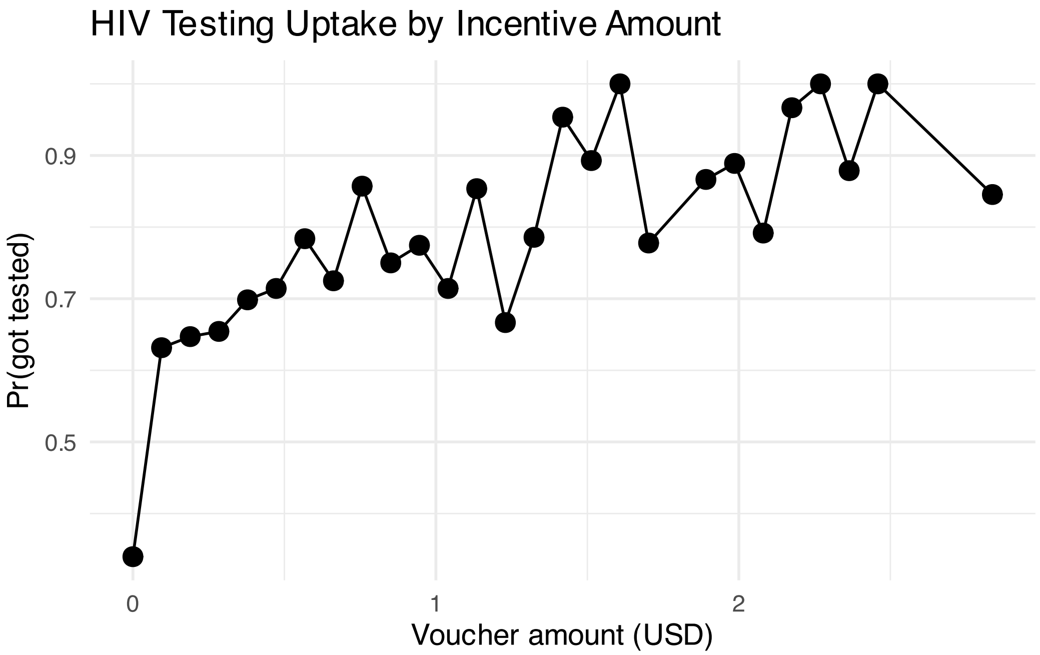
Higher incentive values: - Mean uptake remains high (often above 0.70). - These irregularities are potentially as some incentive levels have very small sample sizes (e.g., n = 7 at tinc ≈ 0.76), making the corresponding means noisy.

Overall: Because voucher amounts were randomly assigned, differences in mean uptake across tinc values can be interpreted causally, subject to SUTVA and random assignment assumptions.

Practically, the results imply that relatively small incentives generate most of the increase in testing uptake, with larger incentives yielding smaller incremental gains.

Graphical visualization of the dose-response relationship: We plot the mean probability of testing against voucher amount to visually assess the relationship.

```
ggplot(by_amount, aes(x = tinc, y = mean_got)) +
geom_point(size = 3) +
geom_line() +
labs(
x = "Voucher amount (USD)",
y = "Pr(got tested)",
title = "HIV Testing Uptake by Incentive Amount"
) +
theme_minimal()
```



Moving from no incentive (tinc = 0) to even very small incentives produces a sharp jump in testing uptake (from ~0.34 to above 0.60). This indicates that the primary behavioral response is driven by the presence of any incentive rather than its size.

This interpretation relies on SUTVA: each individual's outcome depends only on their own voucher assignment, with no spillovers or interference across respondents.

…

Treatment effects by age

You will now analyze the effect of age by adapting the approach we used for educ.

First, create a binarized variable, cutting off age at a value that you can determine. Second, compute the means for control and treatment group for each value of the binarized variable. Interpret your results.

Answer

1. To choose an age of the cutoff range, we use the sample median age. To determine this we will simply use ‘median’ to calculate the median of the sample. Then we will split the sample based off the median into a “younger” and “older” group.

```
median(JC$age, na.rm = TRUE)
```

```
[1] 18
```

```
age_cut <- median(JC$age, na.rm = TRUE)

JC <- JC |>
  mutate(age_high = age >= age_cut)
JC |>
  count(age_high)
```

```
# A tibble: 2 × 2
  age_high     n
  <lgl>    <int>
1 FALSE     3740
2 TRUE      5500
```

The output is that the sample median age is 18. Thus, those in the older group are those aged 18 or older and those in the younger group are 17 and below. Therefore, the sample is now split into a “younger” and “older” group. In the younger group, we have 3740 observations and 5500 observations in the older group. Age_higher = FALSE indicates the younger age group.

2. To compute the means for the control and treatment group for each value of the binarized variable we use ‘group_by’, which groups by ‘age_high’ and ‘assignment’, then ‘summarize’ calculates the mean of ‘earny4’ for these groupings.

```
JC |>
  group_by(age_high, assignment) |>
  summarize(EY = mean(earny4), .groups = "drop") |>
  pivot_wider(names_from = assignment,
              values_from = EY,
              names_prefix = "assign_") |>
  mutate(CATE = assign_1 - assign_0)
```

```
# A tibble: 2 × 4
  age_high assign_0 assign_1  CATE
  <lgl>       <dbl>    <dbl> <dbl>
1 FALSE        177.     188.  11.5
2 TRUE         213.     231.  17.3
```

The CATE is the conditional average treatment effect and shows the difference in mean earnings between the treatment and control conditional on being in the "younger" or "older" age group.

Our results show that the CATE for younger individuals is 11.5. This means that assignment to Jobs Corps increases fourth-year earnings by about 11.5 units for younger individuals. The control mean for younger individuals is about 177 and the treatment mean is about 188.

For older individuals (age_high = TRUE), the control mean is about 213 and the treatment mean is about 231. The CATE is 17.3. Thus, our findings suggest that the increased average earnings is higher for older individuals. This suggests heterogeneous treatment effects by age.

For troubleshooting: do not edit or remove

```
sysname

"Darwin"

release

"25.2.0"

version
"Darwin Kernel Version 25.2.0: Tue Nov 18 21:09:49 PST 2025;
root:xnu-12377.61.12~1/RELEASE_ARM64_T8142"

nodename

"tadhgs-M5-MacBook-Pro.local"

machine

"arm64"

login

"root"

user

"tadhg"

effective_user

"tadhg"
```

```
[1] "2026-02-04 13:21:12 EST"
```