Problem Set 8

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Set-up

```r
library(tidyverse)     # For ggplot, mutate(), filter(), and friends
library(broom)         # For converting models to data frames
library(estimatr)      # For lm_robust() and iv_robust()
library(modelsummary)  # For showing side-by-side regression tables
library(MatchIt)       # For matching
library(rdrobust)      # For nonparametric RD
library(rddensity)     # For nonparametric RD density tests
library(haven)         # For reading Stata files

set.seed(1234)  # Make any random stuff be the same every time you run this

# Round everything to 3 digits by default
options("digits" = 3)

# Turn off the message that happens when you use group_by() and summarize()
options(dplyr.summarise.inform = FALSE)

# Load raw data
hisp_raw <- read_stata("../data/evaluation.dta")

# Make nice clean dataset to use for the rest of the assignment
hisp <- hisp_raw %>%
  # Having a numeric 0/1 column is sometimes helpful for things that don't like
  # categories, like matchit()
  mutate(enrolled_num = enrolled) %>%
  # Convert these 0/1 values to actual categories
  mutate(eligible = factor(eligible, labels = c("Not eligible", "Eligible")),
```

```
        enrolled = factor(enrolled, labels = c("Not enrolled", "Enrolled")),
        round = factor(round, labels = c("Before", "After")),
        treatment_locality = factor(treatment_locality, labels = c("Control", "Treatment"
        promotion_locality = factor(promotion_locality, labels = c("No promotion", "Promo
  # Get rid of this hospital column because (1) we're not using it, and (2) half
  # of the households are missing data, and matchit() complains if any data is
  # missing, even if you're not using it
  select(-hospital)
```

Background

The World Bank's *Impact Evaluation in Practice* has used a hypothetical example of a health insurance program throughout the book. This Health Insurance Subsidy Program (HISP) provides subsidies for buying private health insurance to poorer households, with the goal of lowering personal health expenditures, since people can rely on insurance coverage instead of paying out-of-pocket. Think of the HISP as a version of the Affordable Care Act (ACA, commonly known as Obamacare).

The dataset includes a number of important variables you'll use throughout this assignment:

Variable name	Description
`health_expenditures`	Out of pocket health expenditures (per person per year)
`eligible`	Household eligible to enroll in HISP
`enrolled`	Household enrolled in HISP
`round`	Indicator for before and after intervention
`treatment_locality`	Household is located in treatment community
`poverty_index`	1-100 scale of poverty
`promotion_locality`	Household is located in community that received random promotion
`enrolled_rp`	Household enrolled in HISP following random promotion

It also includes several demographic variables about the households. **Each of these are backdoor confounders between health expenditures participation in the HISP**:

Variable name	Description
`age_hh`	Age of the head of household (years)
`age_sp`	Age of the spouse (years)
`educ_hh`	Education of the head of household (years)
`educ_sp`	Education of the spouse (years)
`female_hh`	Head of household is a woman (1 = yes)

Variable name	Description
`indigenous`	Head of household speaks an indigenous language (1 = yes)
`hhsize`	Number of household members
`dirtfloor`	Home has a dirt floor (1 = yes)
`bathroom`	Home has a private bathroom (1 = yes)
`land`	Number of hectares of land owned by household
`hospital_distance`	Distance to closest hospital (km)

You will use each of the five main econometric approaches for estimating causal effects to measure the effect of HISP on household health expenditures. **Don't worry about conducting in-depth baseline checks and robustness checks.** For the sake of this assignment, you'll do the minimum amount of work for each method to determine the causal effect of the program.

Task 1: RCTs

To measure the effect of HISP accurately, World Bank researchers randomly assigned different localities (villages, towns, cities, whatever) to treatment and control groups. Some localities were allowed to join HISP; others weren't.

```
hisp_eligible <- hisp %>%
  filter(eligible == "Eligible")

hisp_after <- hisp %>%
  filter(round == "After")
```

Below are the average health expenditures for the treatment and control group before the intervention. The control group had an average expenditure of 14.6, and the the treatment group had an average expenditure of 14.5.

```
hisp_eligible %>%
  filter(round == "Before") %>%
  group_by(treatment_locality) %>%
  summarize(mean = mean(health_expenditures))
```

```
# A tibble: 2 x 2
  treatment_locality  mean
  <fct>              <dbl>
```

```
1 Control              14.6
2 Treatment            14.5
```

After the intervention, the control group's average expenditure increases to 17.98 and the the treatment group's average expenditure decreases to 7.84.

```
df <- hisp_eligible %>%
  filter(round == "After") %>%
  group_by(treatment_locality) %>%
  summarize(mean = mean(health_expenditures))
df
```

```
# A tibble: 2 x 2
  treatment_locality  mean
  <fct>              <dbl>
1 Control            18.0
2 Treatment           7.84
```

The treatment group has an average health expenditure that is 10.1 less than the control group after the intervention.

```
diff(df$mean) # Control - Treatment
```

```
[1] -10.1
```

The linear regression shows that the treatment group's expenditure after the intervention is 6.41 less than the control group's.

```
lm_model <- lm_robust(health_expenditures ~ treatment_locality,
           data = hisp_after,
           clusters = locality_identifier)
tidy(lm_model)
```

```
                      term estimate std.error statistic  p.value conf.low
1              (Intercept)    20.06     0.379      52.9 6.81e-48    19.30
2 treatment_localityTreatment    -6.41     0.504     -12.7 3.32e-23    -7.41
  conf.high    df             outcome
1     20.83  53.5 health_expenditures
2     -5.41 108.6 health_expenditures
```

The confounders slightly biased the treatment effect away from zero. When controlling for confounders the treatment effect is 6.12, meaning the treatment group spends 6.12 less than the control group after the intervention.

```
full_linear_model <- lm_robust(health_expenditures ~ treatment_locality + age_hh + age_sp
          data = hisp_after,
          clusters = locality_identifier
          )
tidy(full_linear_model)
```

```
                        term estimate std.error statistic  p.value conf.low
1                  (Intercept) 28.95706   0.80870    35.807 5.46e-58  27.3522
2  treatment_localityTreatment -6.12955   0.40172   -15.258 8.37e-29  -6.9258
3                       age_hh  0.10801   0.01495     7.224 1.15e-10   0.0783
4                       age_sp  0.00799   0.01643     0.486 6.28e-01  -0.0246
5                      educ_hh  0.11265   0.04600     2.449 1.60e-02   0.0214
6                      educ_sp -0.00980   0.05009    -0.196 8.45e-01  -0.1091
7                    female_hh  1.08976   0.47396     2.299 2.37e-02   0.1489
8                   indigenous -2.80641   0.37524    -7.479 4.02e-11  -3.5515
9                       hhsize -2.38237   0.06408   -37.180 5.05e-62  -2.5094
10                   dirtfloor -3.04384   0.29840   -10.201 2.25e-17  -3.6355
11                    bathroom  0.97106   0.25513     3.806 2.41e-04   0.4650
12                        land  0.16545   0.04006     4.130 1.01e-04   0.0855
13          hospital_distance -0.00600   0.00454    -1.320 1.91e-01  -0.0151
   conf.high    df             outcome
1   30.56195  97.7 health_expenditures
2   -5.33334 108.9 health_expenditures
3    0.13769  96.9 health_expenditures
4    0.04059  99.6 health_expenditures
5    0.20387 104.6 health_expenditures
6    0.08953 104.5 health_expenditures
7    2.03059  95.8 health_expenditures
8   -2.06131  93.4 health_expenditures
9   -2.25531 104.4 health_expenditures
10  -2.45215 104.7 health_expenditures
11   1.47710 102.1 health_expenditures
12   0.24538  68.6 health_expenditures
13   0.00306  71.3 health_expenditures
```

```
modelsummary(list(
  "Simple Regression" = lm_model,
```

```
    "Multiple Regression" = full_linear_model
  ),
  title = "Health Expenditure on Helath Insurance Program")
```

Task 2: Inverse probability weighting and/or matching

Naive Model

According to the model below, the people who enrolled in the intervention had 12.9 less in health expenditures compared to the non-enrollees. However, this is an inaccurate representation because it includes both compilers and always-takers.

```
model.naive <- lm(health_expenditures ~ enrolled,
                  data = hisp_after)
tidy(model.naive)
```

```
# A tibble: 2 x 5
  term             estimate std.error statistic p.value
  <chr>               <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)          20.7     0.124     167.        0
2 enrolledEnrolled    -12.9     0.227     -56.8       0
```

Inverse Probability Weighting

$$\frac{\text{Treatment}}{\text{Propensity}} + \frac{1 - \text{Treatment}}{1 - \text{Propensity}}$$

Logistic regression to model the probability of enrolling in the HISP based on demographic features.

```
model_logit <- glm(enrolled ~ age_hh + age_sp + educ_hh + educ_sp + female_hh + indigenous
                   data = hisp_after,
                   family = binomial(link = "logit"))
```

Below we fit the logistic regression model to get the probability of enrollment for each observation. When them mutate the probability to create the *inverse probability weighting ratio* (IPW). This ratio gives observations with with weird outcomes more weight.

Table 3: Health Expenditure on Helath Insurance Program

	Simple Regression	Multiple Regression
(Intercept)	20.064	28.957
	(0.379)	(0.809)
treatment_localityTreatment	−6.406	−6.130
	(0.504)	(0.402)
age_hh		0.108
		(0.015)
age_sp		0.008
		(0.016)
educ_hh		0.113
		(0.046)
educ_sp		−0.010
		(0.050)
female_hh		1.090
		(0.474)
indigenous		−2.806
		(0.375)
hhsize		−2.382
		(0.064)
dirtfloor		−3.044
		(0.298)
bathroom		0.971
		(0.255)
land		0.165
		(0.040)
hospital_distance		−0.006
		(0.005)
Num.Obs.	9914	9914
R2	0.073	0.344
R2 Adj.	0.072	0.343
Std.Errors	by: locality_identifier	by: locality_identifier

```r
enrolled_propensities <- augment_columns(model_logit, hisp_after,
                                         type.predict = "response") %>%
                                          rename(p_enrolled = .fitted)

enrolled_propensities <- enrolled_propensities %>%
  mutate(inverse_prob = (enrolled_num/p_enrolled)+((1-enrolled_num)/(1-p_enrolled))) %>%
  filter(inverse_prob <= 10)
```

A new linear model is used, but this time weights are included.

```r
ipw_model <- lm(health_expenditures ~ enrolled,
                          data = enrolled_propensities,
                          weights = inverse_prob)

tidy(ipw_model)
```

```
# A tibble: 2 x 5
  term             estimate std.error statistic p.value
  <chr>               <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)          19.8     0.134     148.        0
2 enrolledEnrolled    -11.0     0.194     -56.6       0
```

Below the naive model's results show that the effect of being enrolled in the program decreases the health expenditure by 12.87 on average ($p<.01$). The IPW model has a smaller coefficient magnitude of 11.00, meaning that participation in the program decrease health expenditure by 11.00 dollars per year. The IPW model can be assumed to be the causal effect, because it accounts for always-takers, and never-takers.

```r
modelsummary(list(
  "Naive" = model.naive,
  "IPW" = ipw_model
),
title = "Health Expenditures on Health Insurance Program")
```

Task 3: Diff-in-diff

Instead of using experimental data, we can estimate the causal effect using observational data alone with a difference-in-difference approach. We have data indicating if households were enrolled in the program (`enrolled`) and data indicating if they were surveyed before or

Table 4: Health Expenditures on Health Insurance Program

	Naive	IPW
(Intercept)	20.707	19.830
	(0.124)	(0.134)
enrolledEnrolled	−12.867	−11.002
	(0.227)	(0.194)
Num.Obs.	9914	9869
R2	0.246	0.245
R2 Adj.	0.245	0.245
AIC	74 435.6	73 846.1
BIC	74 457.2	73 867.7
Log.Lik.	−37 214.778	−36 920.046
F	3225.402	3203.813
RMSE	10.33	13.41

after the intervention (`round`), which means we can find the differences between enrolled/not enrolled before and after the program.

```
hisp_tr <- hisp %>% filter(treatment_locality == "Treatment")
```

Results of the robust difference-and-difference model show that the causal effect of program enrollment reduces health expenditures by 8.16.

```
dd_model <- lm_robust(health_expenditures ~ enrolled + round + enrolled * round,
                      data = hisp_tr,
                      clusters = locality_identifier)
tidy(dd_model)
```

```
                      term estimate std.error statistic  p.value conf.low
1                (Intercept)    20.79     0.174    119.76 2.56e-59    20.44
2           enrolledEnrolled    -6.30     0.194    -32.40 1.54e-36    -6.69
3                 roundAfter     1.51     0.360      4.21 1.17e-04     0.79
4 enrolledEnrolled:roundAfter    -8.16     0.321    -25.44 2.53e-31    -8.81
  conf.high   df             outcome
1     21.14 46.3 health_expenditures
2     -5.91 52.8 health_expenditures
3      2.24 46.3 health_expenditures
4     -7.52 52.8 health_expenditures
```

When controlling for other factors in the difference-and-difference model, we see that the causal

effect of program enrollment does not change ($\beta = -8.16$).

```
dd_multi_model <- lm_robust(health_expenditures ~ enrolled + round + enrolled * round + ag
                      data = hisp_tr,
                      clusters = locality_identifier)
tidy(dd_multi_model)
```

```
                         term estimate std.error statistic  p.value conf.low
1                 (Intercept) 27.39458   0.56144     48.79 6.16e-45 26.26784
2             enrolledEnrolled -1.51276   0.13019    -11.62 2.76e-16 -1.77380
3                  roundAfter  1.45053   0.35889      4.04 1.99e-04  0.72822
4                      age_hh  0.08049   0.01150      7.00 9.02e-09  0.05734
5                      age_sp -0.01972   0.01310     -1.51 1.39e-01 -0.04607
6                     educ_hh  0.05999   0.02932      2.05 4.56e-02  0.00121
7                     educ_sp -0.07651   0.03426     -2.23 2.98e-02 -0.14526
8                   female_hh  1.10393   0.31800      3.47 1.09e-03  0.46485
9                   indigenous -2.31199   0.23919     -9.67 4.59e-13 -2.79231
10                     hhsize -1.99473   0.03942    -50.60 3.74e-47 -2.07376
11                  dirtfloor -2.29984   0.16464    -13.97 2.54e-19 -2.63014
12                   bathroom  0.50004   0.15950      3.14 2.84e-03  0.17990
13                       land  0.09090   0.02908      3.13 3.67e-03  0.03175
14          hospital_distance -0.00319   0.00311     -1.02 3.12e-01 -0.00949
15 enrolledEnrolled:roundAfter -8.16150   0.32125    -25.41 2.73e-31 -8.80590
   conf.high   df             outcome
1   28.52132 51.7 health_expenditures
2   -1.25172 53.8 health_expenditures
3    2.17283 46.3 health_expenditures
4    0.10363 46.1 health_expenditures
5    0.00662 47.4 health_expenditures
6    0.11878 53.5 health_expenditures
7   -0.00777 52.0 health_expenditures
8    1.74302 48.8 health_expenditures
9   -1.83166 50.4 health_expenditures
10  -1.91570 54.0 health_expenditures
11  -1.96954 52.5 health_expenditures
12   0.82019 51.5 health_expenditures
13   0.15005 33.2 health_expenditures
14   0.00311 39.2 health_expenditures
15  -7.51710 52.8 health_expenditures
```

```
modelsummary(list(
  "DD" = dd_model,
  "Multi variate DD" = dd_multi_model
),
title = "Health Expenditures on Health Insurance Program")
```

Task 4: RDD

Eligibility for the HISP is determined by income. Households that have an income of less than 58 on a standardized 1-100 scale (`poverty_index`) qualify for the program and are automatically enrolled. Because we have an arbitrary cutoff in a running variable, we can use regression discontinuity to measure the effect of the program on health expenditures.

Use `mutate()` to add new variable that centers the poverty index variable at 58

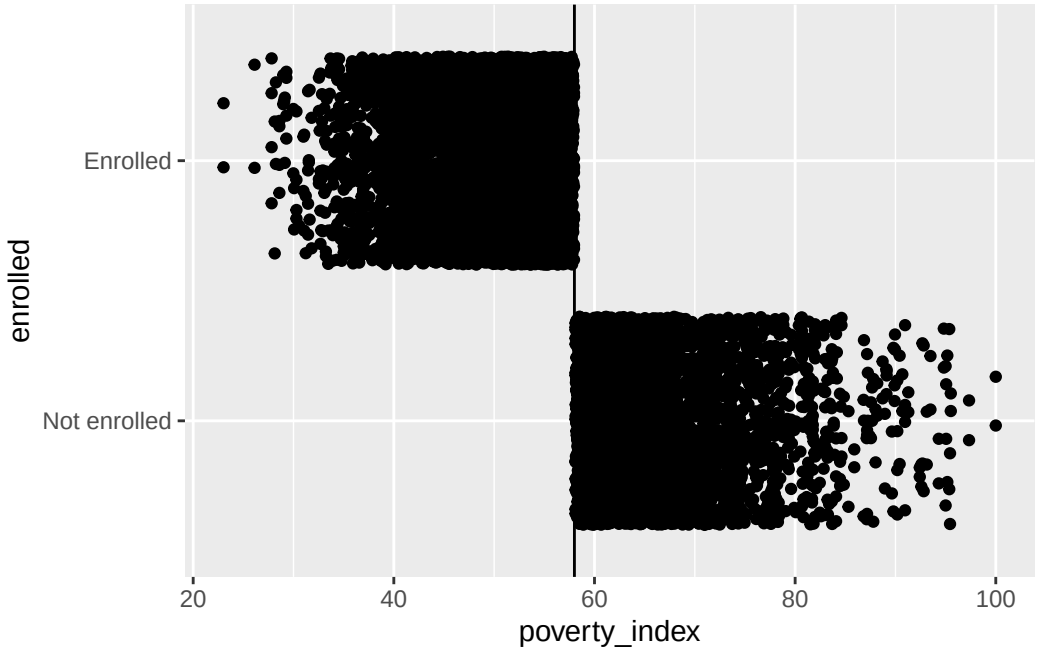
```
hisp_tr <- hisp_tr %>% mutate(
  poverty_index_centered = poverty_index - 58
)
```

Determine if the discontinuity is sharp or fuzzy. (Hint: create a scatterplot with `poverty_index` on the x-axis, `enrolled` on the y-axis, and a vertical line at 58.)

```
ggplot(hisp_tr) +
  geom_jitter(aes(poverty_index,enrolled)) +
  geom_vline(xintercept = 58)
```

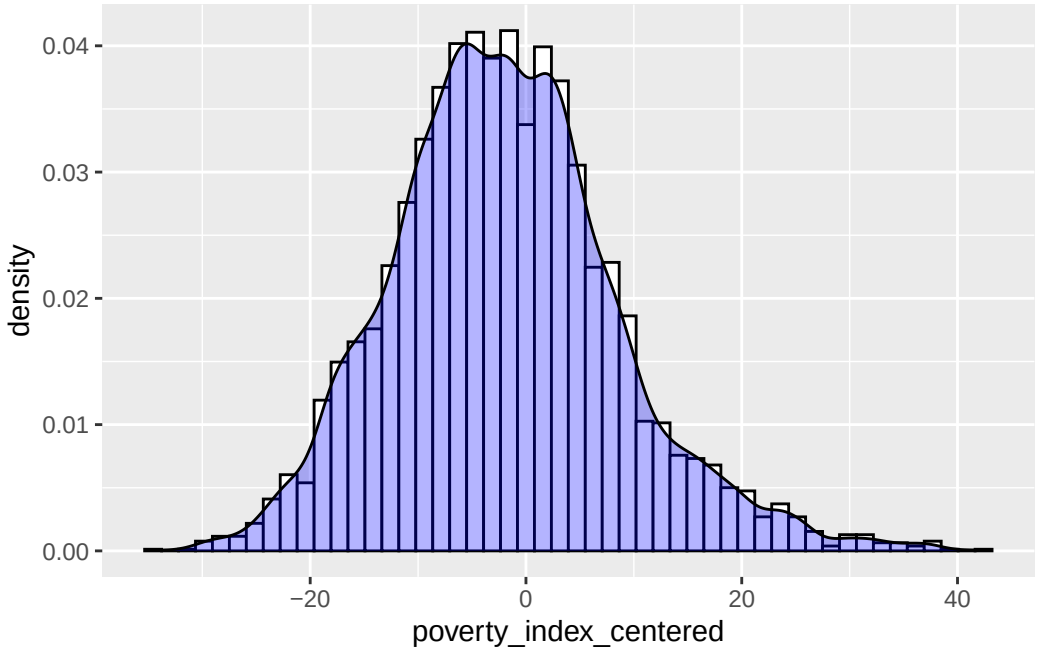
Table 5: Health Expenditures on Health Insurance Program

	DD	Multi variate DD
(Intercept)	20.791	27.395
	(0.174)	(0.561)
enrolledEnrolled	−6.302	−1.513
	(0.194)	(0.130)
roundAfter	1.513	1.451
	(0.360)	(0.359)
enrolledEnrolled × roundAfter	−8.163	−8.161
	(0.321)	(0.321)
age_hh		0.080
		(0.011)
age_sp		−0.020
		(0.013)
educ_hh		0.060
		(0.029)
educ_sp		−0.077
		(0.034)
female_hh		1.104
		(0.318)
indigenous		−2.312
		(0.239)
hhsize		−1.995
		(0.039)
dirtfloor		−2.300
		(0.165)
bathroom		0.500
		(0.160)
land		0.091
		(0.029)
hospital_distance		−0.003
		(0.003)
Num.Obs.	9919	9919
R2	0.344	0.552
R2 Adj.	0.343	0.551
Std.Errors	by: locality_identifier	by: locality_identifier



Determine if the distribution of the running variable (`poverty_index`) has a jump near the cutoff (it shouldn't). (Hint: create a histogram with `poverty_index` on the x-axis and a vertical line at 58. Use a McCrary test to see if there's a significant break in the distribution at 58.)

```
ggplot(hisp_tr) +
  geom_histogram(aes(poverty_index_centered, ..density..), bins = 50, color = "black", fil
  geom_density(aes(poverty_index_centered), fill = "blue", alpha = .3)
```




```r
denstest <- rddensity(hisp_tr$poverty_index_centered, c = 0)
summary(denstest)
```

```
Manipulation testing using local polynomial density estimation.

Number of obs =       9919
Model =               unrestricted
Kernel =              triangular
BW method =           estimated
VCE method =          jackknife

c = 0                 Left of c           Right of c
Number of obs         5929                3990
Eff. Number of obs    1858                1992
Order est. (p)        2                   2
Order bias (q)        3                   3
BW est. (h)           4.81                5.673

Method                T                   P > |T|
Robust                -0.6822             0.4951
```

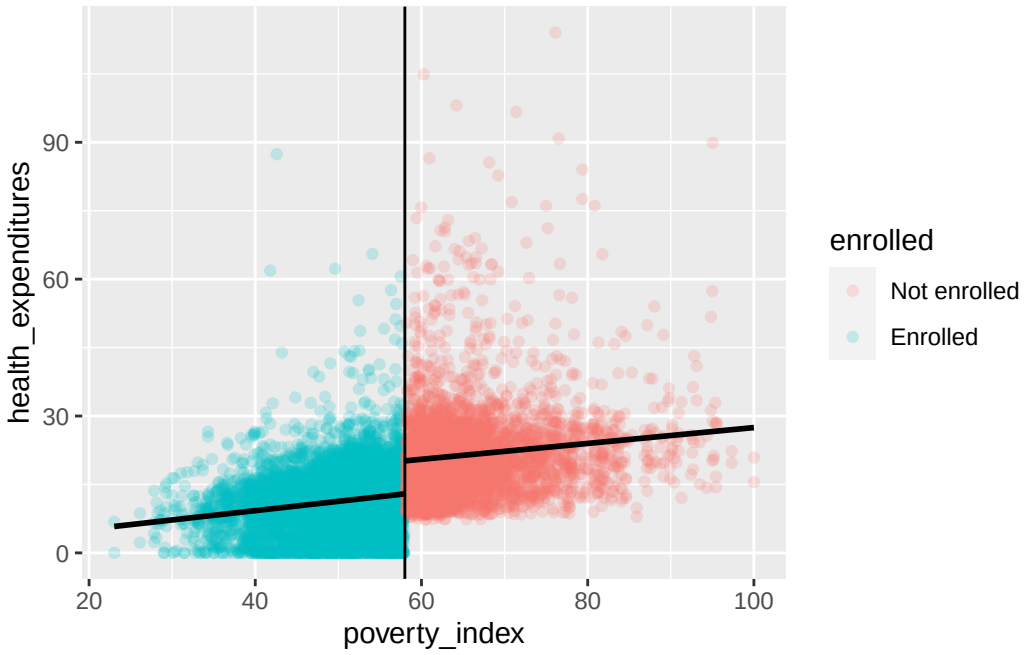
```
P-values of binomial tests (H0: p=0.5).

Window Length / 2          <c     >=c    P>|T|
0.114                       16      14    0.8555
0.229                       58      32    0.0080
0.343                       98      66    0.0152
0.457                      148     122    0.1280
0.572                      186     160    0.1789
0.686                      242     202    0.0641
0.801                      274     254    0.4083
0.915                      320     288    0.2086
1.029                      362     318    0.0991
1.144                      428     376    0.0720
```

Visualize the jump in outcome at the cutoff with a scatterplot (Hint: create a scatterplot with `poverty_index` on the x-axis, `health_expenditures` on the y-xis, color by `enrolled`, add a vertical line at 58, and add trendlines with `geom_smooth(method = "lm")`. You might want to adjust the size and transparency of the points with `geom_point(alpha = 0.2, size = 0.2)` or something similar.)

From the graph below, we can see a distinct jump in health expenditures above the cutoff, however statistical significance is still in question.

```r
ggplot(hisp_tr, mapping = aes(poverty_index, health_expenditures, color = enrolled)) +
  geom_point(alpha = .2) +
  geom_vline(xintercept = 58) +
  geom_smooth(aes(group=enrolled), method = "lm", color = "black", se = F)
```



Build a parametric regression model to estimate the size of the gap at the cutoff. You'll want to use the centered policy index variable to make it easier to interpret. You probably want to create a new dataset that only includes observations within some bandwidth that you choose (`filter(poverty_index_centered >= SOMETHING & poverty_index_centered <= SOMETHING)`). How big is the effect?

From the results below, we see that program enrollment reduces health expenditures by 6.81.

```
rdd_model <- lm(health_expenditures ~ poverty_index_centered + enrolled,
                data = filter(hisp_tr, poverty_index_centered < 10, poverty_index_centered

tidy(rdd_model)
```

```
# A tibble: 3 x 5
  term                   estimate std.error statistic  p.value
  <chr>                     <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)              20.0      0.220      90.8  0
2 poverty_index_centered    0.236    0.0367      6.45 1.21e-10
3 enrolledEnrolled         -6.82     0.392     -17.4  2.90e-66
```

Use `rdrobust()` from the **rdrobust** library to estimate the size of the gap nonparametrically. For the sake of simplicity, just use the default (automatic) bandwidth and kernel. How big is the effect?

From the results below, we see that program enrollment reduces health expenditures by 6.52.

```
rdrobust(y = hisp_tr$health_expenditures, x = hisp_tr$poverty_index_centered, c = 0) %>%
  summary()
```

```
Sharp RD estimates using local polynomial regression.

Number of Obs.                 9919
BW type                       mserd
Kernel                   Triangular
VCE method                       NN

Number of Obs.                 5929         3990
Eff. Number of Obs.            2498         2130
Order est. (p)                    1            1
Order bias  (q)                   2            2
BW est. (h)                   6.359        6.359
BW bias (b)                  10.803       10.803
rho (h/b)                     0.589        0.589
Unique Obs.                     717          669

===============================================================================
        Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
===============================================================================
  Conventional     6.523     0.512    12.729     0.000     [5.519 , 7.528]
        Robust         -         -    10.590     0.000     [5.236 , 7.614]
===============================================================================
```

Task 5: IVs/2SLS

Finally, we can use an instrument to remove the endogeneity from the choice to enroll in the HISP and estimate the causal effect from observational data. As you read in chapter 5, World Bank evaluators randomly selected households to receive encouragement to enroll in HISP. You can use this encouragement as an instrument for enrollment.

Build a naive regression model that estimates the effect of HISP enrollment on health expenditures. You'll need to use the `enrolled_rp` variable instead of `enrolled`, since we're measuring enrollment after the encouragement intervention. (Hint: you'll want to use `health_expenditures ~ enrolled_rp`.) What does this naive model tell us about the effect of enrolling in HISP?

The naive model shows the Intent to Treat (ITT) effect of program enrollment on health expenditures ($\beta = -12.7$). Also, this can be interpreted as the effect of encouragement on health expenditure.

```
naive_model <- lm(health_expenditures ~ enrolled_rp,
                  data = hisp_after)
tidy(naive_model)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic p.value
  <chr>          <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)     20.6     0.124     166.         0
2 enrolled_rp    -12.7     0.229     -55.5        0
```

Check the relevance, exclusion, and exogeneity of promotion (`promotion_locality`) as an instrument. For relevance, you'll want to run a model that predicts enrollment based on promotion (hint: `enrolled_rp ~ promotion_locality`) and check (1) the significance of the coefficient and (2) the F-statistic. For exclusion and exogeneity, you'll have to tell a convincing story that proves promotion influences health expenditures *only through* HISP enrollment.

Relevance

The coefficient is significant and the f-stat is greater than 10.

```
relevance <- lm(enrolled_rp ~ promotion_locality,
        data = hisp_after,
        )
tidy(relevance)
```

```
# A tibble: 2 x 5
  term                        estimate std.error statistic  p.value
  <chr>                          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)                   0.0842   0.00586      14.4 1.97e-46
2 promotion_localityPromotion   0.408    0.00818      49.8 0
```

```
glance(relevance)
```

```
# A tibble: 1 x 12
  r.squared adj.r.squared sigma statistic p.value    df logLik    AIC    BIC
```

```
      <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>  <dbl>  <dbl>  <dbl>
1     0.200         0.200 0.407     2485.       0     1 -5158. 10322. 10343.
# ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Exclusion & Endogeneity

Randomized encouragement passes both the exclusion and endogeneity assumption, because of its inherit "randomness". This means that no other variables are correlated with it except for `enrollment_rp` and `health_expenditures` through `enrollment_rp`

Run a 2SLS regression model with promotion as the instrument. You can do this by hand if you want (i.e. run a first stage model, extract predicted enrollment, and use predicted enrollment as the second stage), *or* you can just use the `iv_robust()` function from the **estimatr** library. (Hint: you'll want to use `health_expenditures ~ enrolled_rp | promotion_locality` as the formula). After removing the endogeneity from enrollment, what is the casual effect of enrollment in the HISP on health expenditures?

From the model below, we can see that program enrollment, instrumented by program encouragement, causes a 9.5 decrease in health expenditure.

```
iv_model <- iv_robust(health_expenditures ~ enrolled_rp | promotion_locality,
                      data = hisp_after)

tidy(iv_model)
```

```
        term estimate std.error statistic  p.value conf.low conf.high   df
1 (Intercept)     19.6     0.181     108.8 0.00e+00     19.3     20.00 9912
2 enrolled_rp     -9.5     0.516     -18.4 2.29e-74    -10.5     -8.49 9912
             outcome
1 health_expenditures
2 health_expenditures
```

- Show the results from the two regressions in a side-by-side table if you want

```
modelsummary(list(
  "Naive" = naive_model,
  "IV" = iv_model
),
title = "Health Expenditures on Health Insurance Program")
```

Table 6: Health Expenditures on Health Insurance Program

	Naive	IV
(Intercept)	20.587	19.646
	(0.124)	(0.181)
enrolled_rp	−12.708	−9.500
	(0.229)	(0.516)
Num.Obs.	9914	9914
R2	0.237	0.222
R2 Adj.	0.237	0.222
AIC	74 549.2	
BIC	74 570.8	
Log.Lik.	−37 271.617	
F	3075.623	
RMSE	10.39	
Std.Errors		HC2
statistic.endogeneity		
p.value.endogeneity		
statistic.weakinst		
p.value.weakinst		
statistic.overid		
p.value.overid		

Task 6: Summary

Model	Beta
Naive	-12.7
IPW	-11.0
Diff-in-Diff	-8.16
RDD	-6.81
IV	-9.5

All of the models yield the same conclusion that program enrollment significantly reduces the amount of health expenditures paid. There is a question of by out much. One could argue that the true effect is in the range of -6.81 and -12.7.