

# IV II & RDD II

## Session 12

PMAP 8521: Program evaluation  
Andrew Young School of Policy Studies

# Plan for today

**Treatment effects and compliance**

**Randomized promotion**

**Fuzzy regression discontinuity**

# Treatment effects and compliance

# Potential outcomes

$$\delta = (Y | P = 1) - (Y | P = 0)$$

$\delta$  (delta) = causal effect

P = Program

Y = Outcome

$$\delta = Y_1 - Y_0$$

## Fundamental problem of causal inference

$\delta_i = Y_i^1 - Y_i^0$  in real life is  $\delta_i = Y_i^1 - ???$

Individual-level effects are  
impossible to observe!

# Average treatment effect

Difference between average/expected value when program is on vs. expected value when program is off

$$\text{ATE} = E(Y_1 - Y_0) = E(Y_1) - E(Y_0)$$

Can be found for a whole population, on average

$$\delta = (\bar{Y} \mid P = 1) - (\bar{Y} \mid P = 0)$$

**Every individual has a  
treatment/causal effect**

**ATE = average of all  
unit-level causal effects**

**ATE = Average effect  
for the whole population**

# Other versions of causal effects

Average treatment on the treated

ATT/TOT

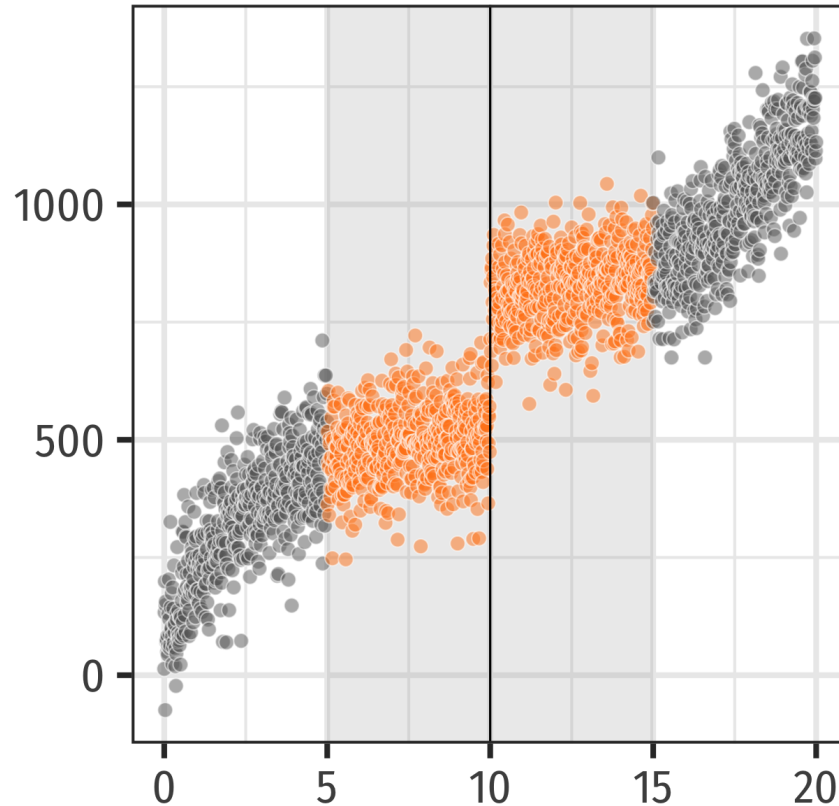
Conditional average treatment effect

CATE

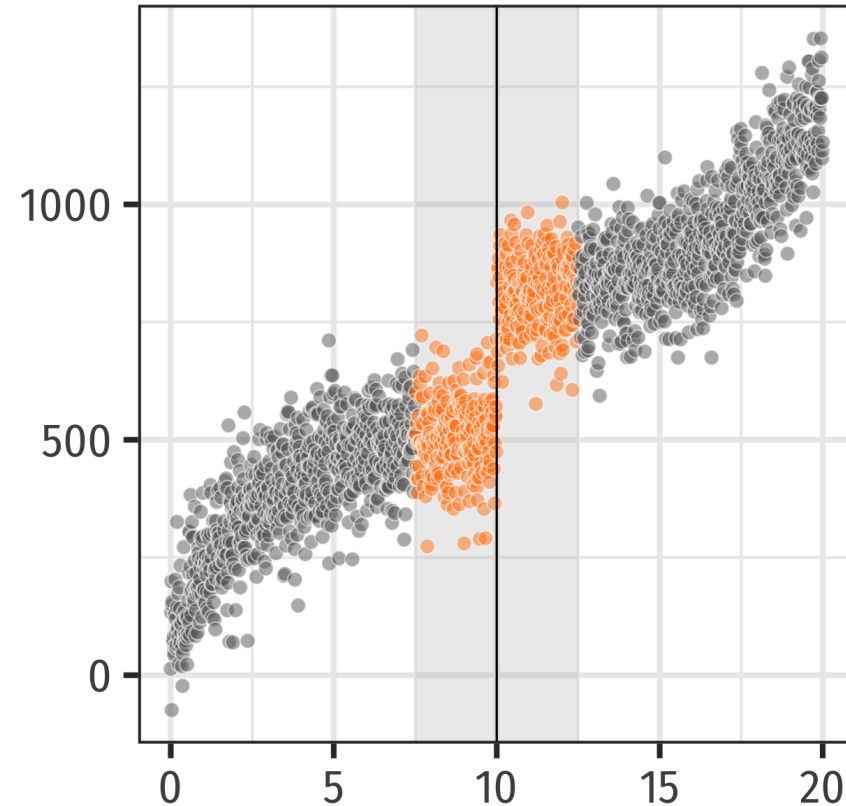


# Local effects

**Bandwidth = 5**



**Bandwidth = 2.5**



# LATE

**Local average treatment effect (LATE) =  
weighted ATE**

**Narrower effect; only applies to some of the population**

**You can't make population-level  
claims with LATE**

**(But that can be okay!)**

# LATE

**In RDD, LATE = people in the bandwidth**

**In RCTs and IVs, LATE = compliers**

# Compliance

**Complier**

**Treatment follows assignment**

**Always taker**

**Gets treatment regardless of assignment**

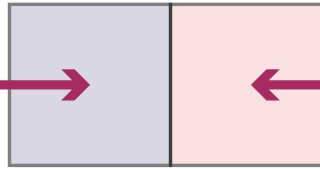
**Never taker**

**Rejects treatment regardless of assignment**

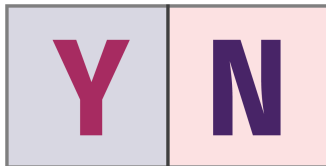
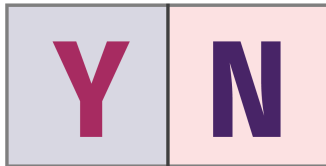
**Defier**

**Does the opposite of assignment**

Choice if assigned to treatment



Choice if assigned to control



**Compliers**



**Always takers**



**Never takers**

# Ignoring defiers

**We can generally assume that defiers don't exist**

**In drug trials this makes sense; you can't get access to medicine without being in treatment group**

**In development it can make sense; in a bed net RCT, a defier assigned to treatment would have to tear down all existing bed nets out of spite**

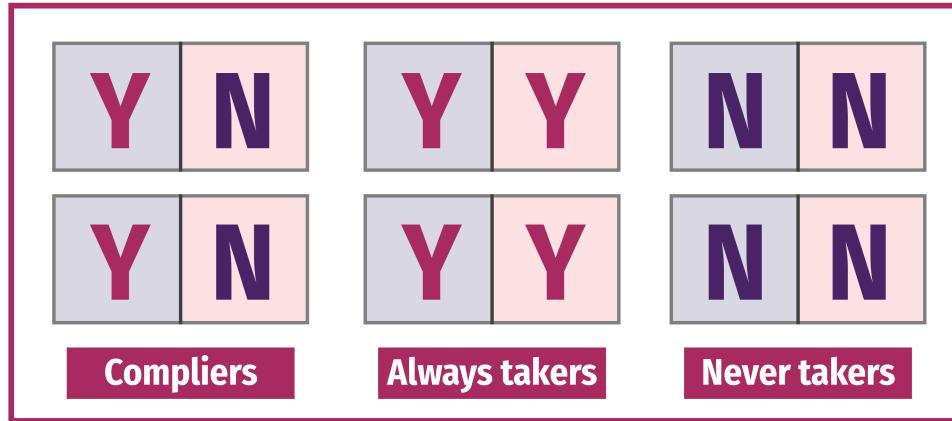
# Ignoring defiers

## Monotonicity assumption

Assignment to treatment only  
has an effect in one direction

Assignment to treatment can only  
increase—not decrease—your actual chance of treatment

**Population**



**Assigned to treatment**

**Assigned to control**

**Compliers +  
always takers**



**Always takers**

**Never takers**



**Compliers +  
never takers**



# More causal effects

## Intent to treat (ITT)

Effect of assignment (not actual treatment!)

### Assigned to treatment

Compliers +  
always takers



Never takers



### Assigned to control



Always takers



Compliers +  
never takers

# More causal effects

## Complier Average Causal Effect (CACE)

LATE for the compliers

Assigned to treatment

Compliers -  
always takers



Never takers



Assigned to control



Always takers



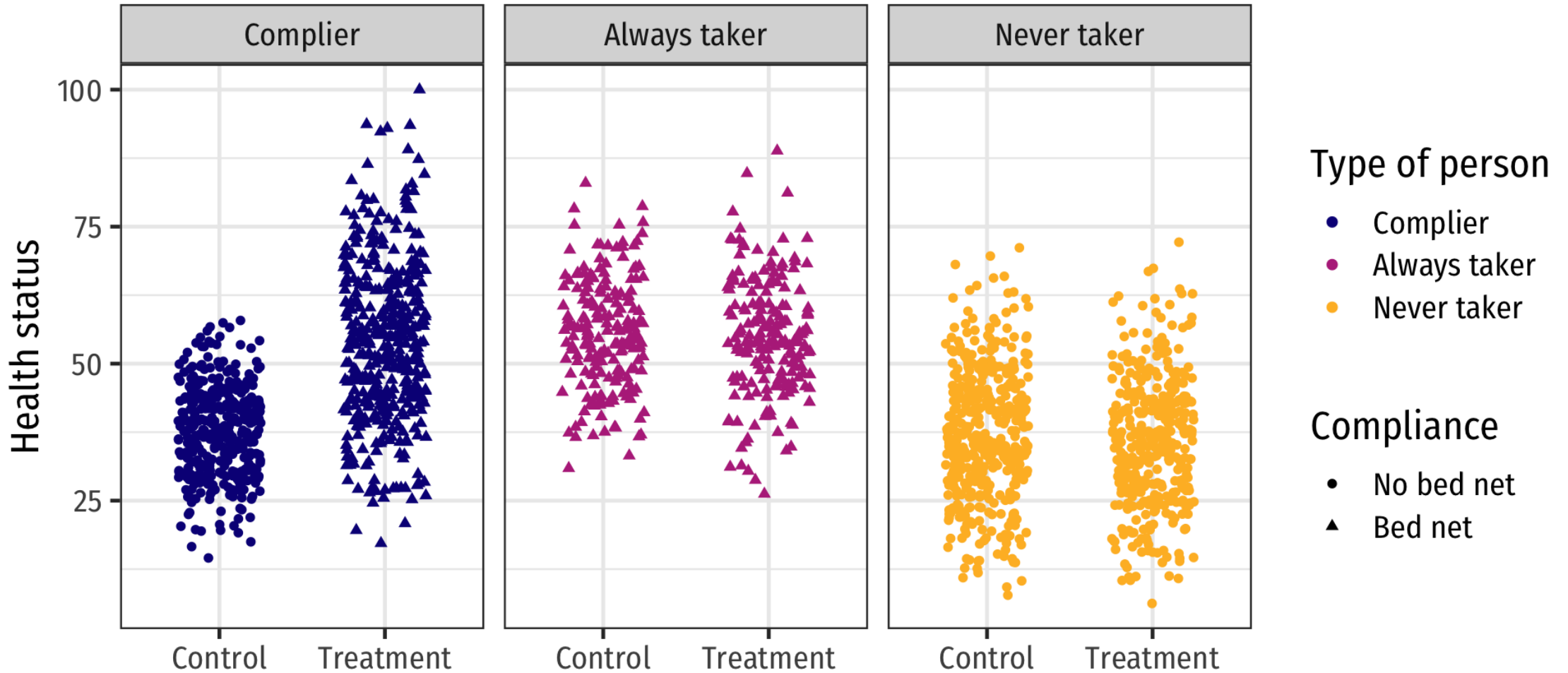
Compliers +  
never takers

# Hypothetical bed net program

**An NGO distributes mosquito bed nets to help improve health by reducing malaria infection rate**

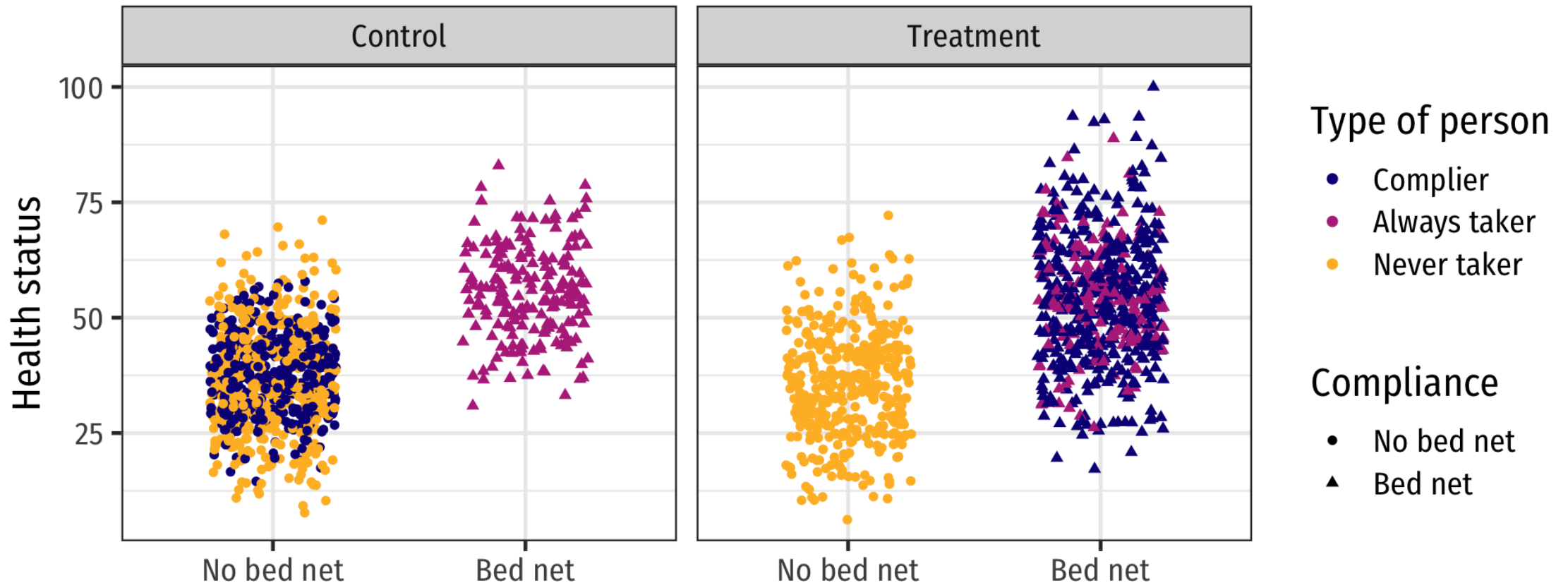
**We can read everyone's minds and we know if people are always takers, never takers, or compliers**

# Mind reading



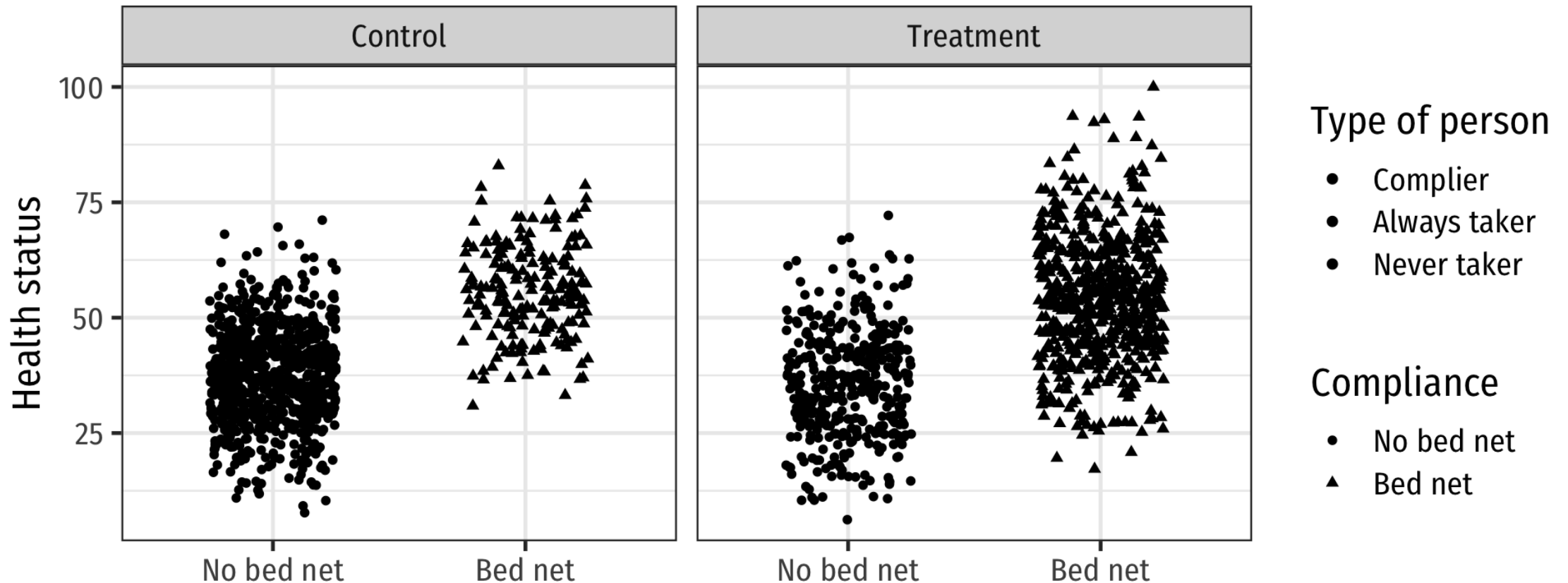
# Actual data

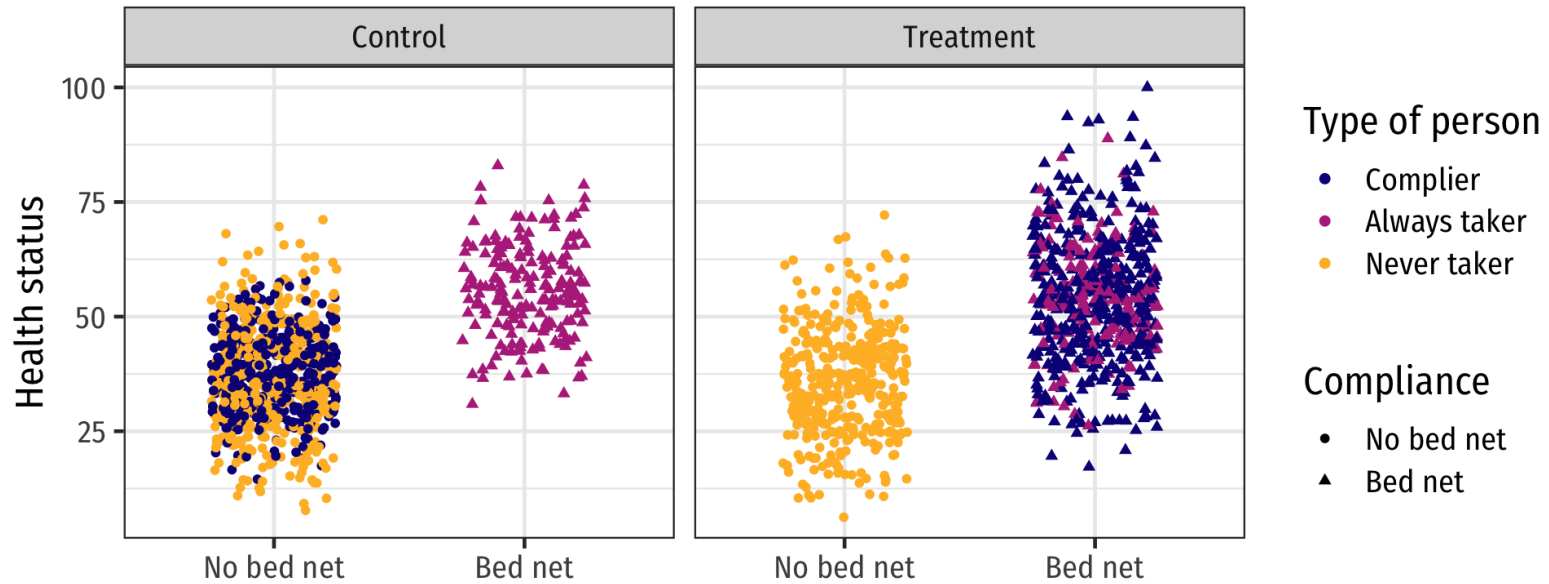
But we can't read minds! This is what we actually see:



# Actual data

(Actually *this* is what we see)



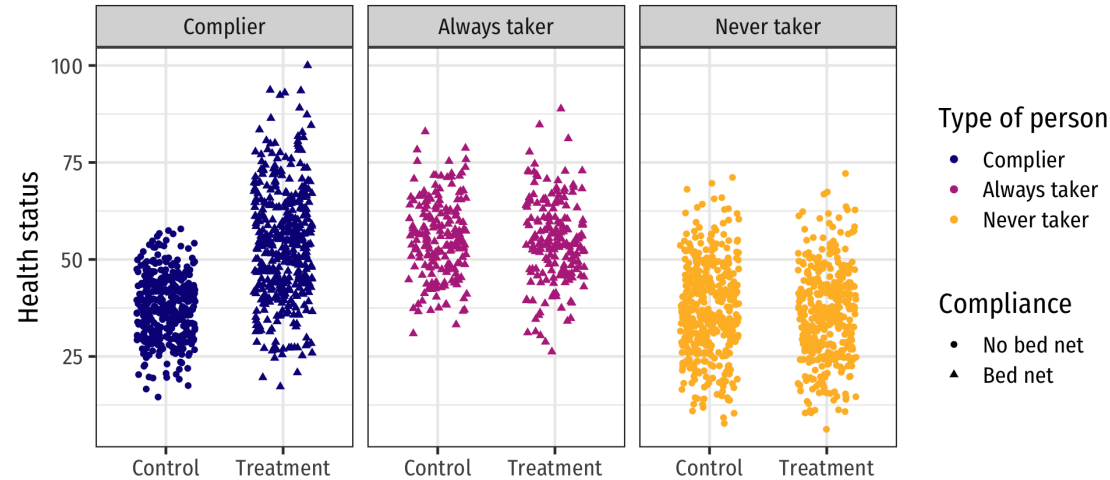


## Assigned to control



## Assigned to treatment

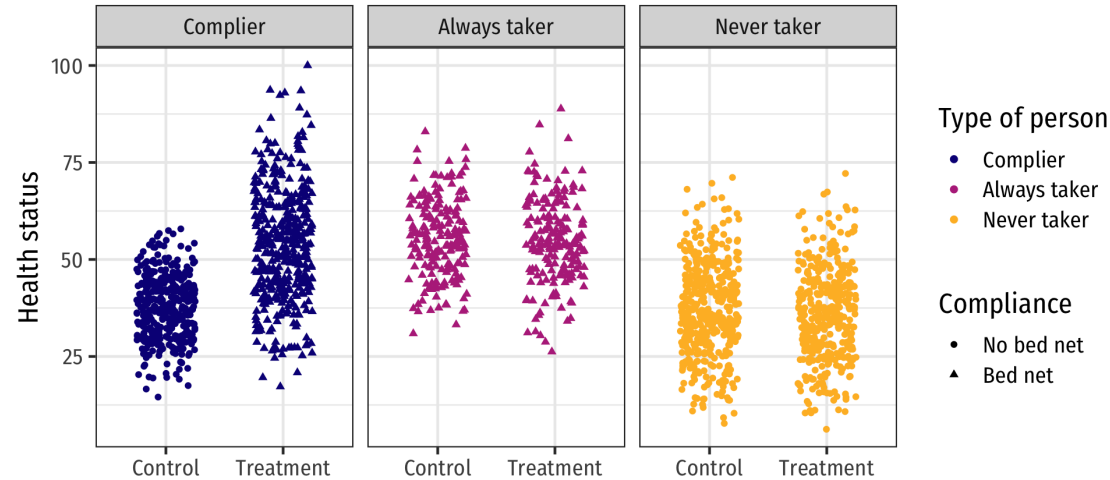




$$\begin{aligned}
 \text{ITT} = & \pi_{\text{compliers}} \times (\text{T} - \text{C})_{\text{compliers}} + \\
 & \pi_{\text{always takers}} \times (\text{T} - \text{C})_{\text{always takers}} + \\
 & \pi_{\text{never takers}} \times (\text{T} - \text{C})_{\text{never takers}}
 \end{aligned}$$

$$\text{ITT} = \pi_C \text{CACE} + \pi_A \text{ATACE} + \pi_N \text{NTACE}$$





$$ITT = \pi_C CACE + \pi_A ATACE + \pi_N NTACE$$

**Treatment received is same regardless of assignment!  
Being assigned to treatment doesn't influence ATs and NTs**

$$ITT = \pi_C CACE + \pi_A \times 0 + \pi_N \times 0$$

$$\text{ITT} = \pi_C \text{CACE} + \pi_A \text{ATA} + \pi_N \text{NTA}$$

$$= \pi_C \text{CACE} + \pi_A \times 0 + \pi_N \times 0$$

$$\text{ITT} = \pi_C \text{CACE}$$

$$\text{CACE} = \frac{\text{ITT}}{\pi_C}$$

**ITT and  $\pi_C$  are both findable!**

# Finding the ITT

ITT = effect of assignment to treatment on outcome

$$\text{ITT} = (\bar{y} \mid \text{Treatment}) - (\bar{y} \mid \text{Control})$$

```
bed_nets %>%  
  group_by(treatment) %>%  
  summarize(avg = mean(health))
```

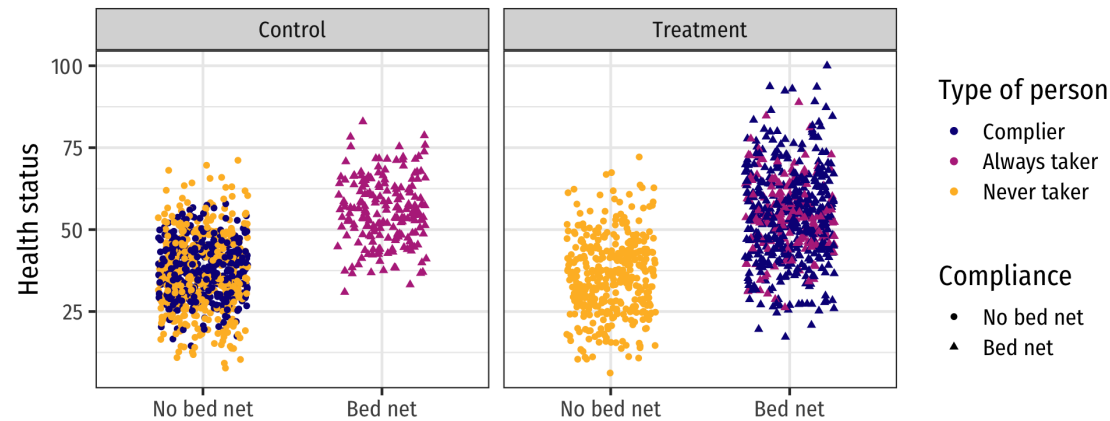
```
## # A tibble: 2 × 2  
##   treatment avg  
##   <chr>     <dbl>  
## 1 Control  40.9  
## 2 Treatment 46.9
```

```
itt_model <- lm(health ~ treatment,  
               data = bed_nets)  
tidy(itt_model)
```

```
## # A tibble: 2 × 2  
##   term                estimate  
##   <chr>                <dbl>  
## 1 (Intercept)          40.9  
## 2 treatmentTreatment  5.99
```

# Finding the $\pi_C$

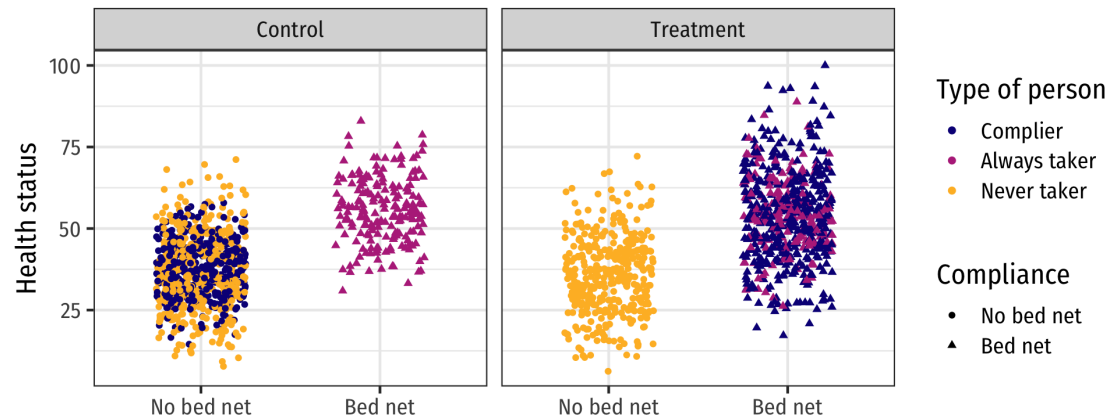
People in treatment group who complied are a combination of Always Takers and Compliers



$$\pi_A + \pi_C = \% \text{ yes in treatment; or}$$
$$\pi_C = \% \text{ yes in treatment} - \pi_A$$

# Can we know $\pi_A$ ?

$$\pi_C = \% \text{ yes in treatment} - \pi_A$$



We can assume that the proportion of Always Takers is the same across treatment and control

We know how many people were in control but still used nets—that's  $\pi_A$ !

# Isolating $\pi_C$

$$\begin{aligned}\pi_C &= \% \text{ yes in treatment} - \pi_A \\ &= \% \text{ yes in treatment} - \% \text{ yes in control}\end{aligned}$$

```
bed_nets %>%  
  group_by(treatment, bed_net) %>%  
  summarize(n = n()) %>%  
  mutate(prop = n / sum(n))
```

```
## # A tibble: 4 × 4  
## # Groups:   treatment [2]  
##   treatment bed_net      n prop  
##   <chr>      <fct>    <int> <dbl>  
## 1 Control   No bed net   808 0.805  
## 2 Control   Bed net     196 0.195  
## 3 Treatment No bed net   388 0.390  
## 4 Treatment Bed net     608 0.610
```

```
# pi_c = prop yes in treatment -  
#         prop yes in control  
pi_c <- 0.6104418 - 0.1952191  
pi_c
```

```
## [1] 0.4152227
```

**41.5% compliers!**

# Finding the CACE, finally!

$$\text{CACE} = \frac{\text{ITT}}{\pi_C}$$

```
ITT <- tidy(itt_model) %>%  
  filter(term == "treatmentTreatment") %>%  
  pull(estimate)  
ITT
```

```
## [1] 5.987992
```

```
pi_c
```

```
## [1] 0.4152227
```

```
CACE <- ITT / pi_c  
CACE
```

```
## [1] 14.42116
```

**Bed nets *cause* 14.4 point  
increase in health for compliers**

$$\text{CACE} = \frac{\text{ITT}}{\pi_C}$$

$$\text{ITT} = (\bar{y} \mid \text{Treatment}) - (\bar{y} \mid \text{Control})$$

$$\pi_C = \% \text{ yes in treatment} - \% \text{ yes in control}$$



# A faster way with 2SLS

## LATE for the compliers

If you use assignment to treatment as an instrument, you can find the causal effect for just compliers

Instrumental variables in general give you the CACE

# CACE with 2SLS

```
model_2sls <- iv_robust(health ~ bed_net | treatment,  
                        data = bed_nets)  
  
tidy(model_2sls)
```

```
##           term estimate std.error statistic      p.value  
## 1 (Intercept) 38.12285 0.5150818  74.01320 0.0000000e+00  
## 2 bed_netBed net 14.42116 1.2538198  11.50178 1.086989e-29
```

**Same 14.421 effect!**

# Promotion as an instrument

# Universal programs

What if you have a program that anyone can opt in to?

ACA, voting, employer retirement matching

You can't just look at outcomes of participants vs. non-participants!

**Selection bias!**

You can't randomly assign people to it either

**Ethics!**

# Randomized promotion

What if you *encourage* some people to participate?

What if the encouragement is randomized?

Valid treatment/control groups?

Not really...

# Randomized promotion

**...but also, kind of!**

**Encouragement/promotion =  
an instrument!**

# Not something weird? Does that work!?

**Relevant?**

$$Z \rightarrow X \quad \text{Cor}(Z, X) \neq 0$$

**Promotion causes people to use the program. Yep.**

**Exclusive?**

$$Z \rightarrow X \rightarrow Y \quad Z \not\rightarrow Y \quad \text{Cor}(Z, Y | X) = 0$$

**Promotion causes outcome *only through* program? Yep.**

**Exogenous?**

$$U \not\rightarrow Z \quad \text{Cor}(Z, U) = 0$$

**Unobserved things that influence outcome don't also influence promotion?  
Yep.**

# Program compliance

**Always Takers**

**People who will always enroll in program**

**Never Takers**

**People who will never enroll in program**

**Compliers / Enrollers-if-Promoted**

**People who will enroll in the program if encouraged to**



# LATE for compliers

id	outcome	program	promotion
1	45	TRUE	TRUE
2	55	TRUE	FALSE
3	52	FALSE	FALSE
4	39	FALSE	TRUE

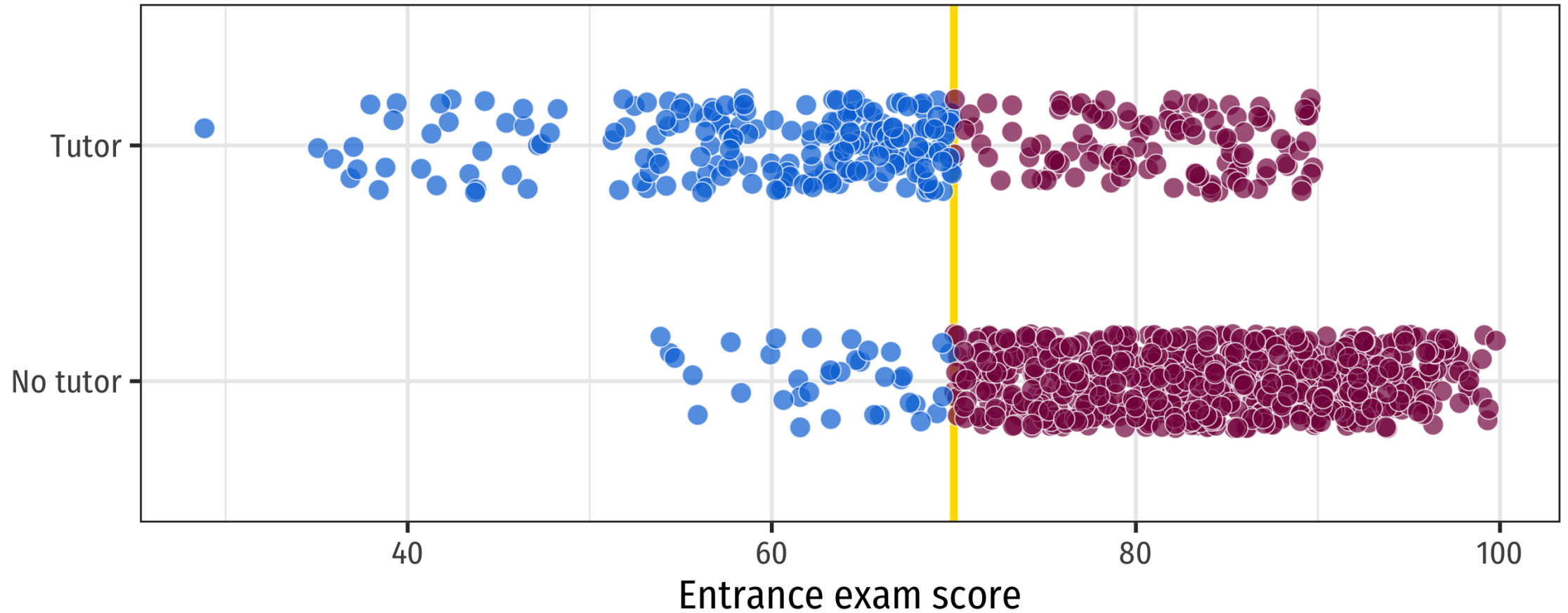
```
iv_robust(outcome ~ program | promotion)
```

**This will show the LATE for promoted-ees!**

**Says nothing about the effect of the program on Always Takers or Never Takers**

# Fuzzy RDD

# Fuzzy discontinuities



Entrance exam  $\leq 70$  ● TRUE ● FALSE

# Fuzzy discontinuities

**Fuzzy discontinuities imply noncompliance**

**Address noncompliance with  
instrumental variables**

# What do we use as instrument?

**Instrument = above/below cutoff**

**i.e. what they were supposed to do**

**(This is just like the CACE we just did!)**

# Not something weird? Does that work!?

Relevant?

$$Z \rightarrow X \quad \text{Cor}(Z, X) \neq 0$$

Cutoff causes program? Yep.

Exclusive?

$$Z \rightarrow X \rightarrow Y \quad Z \not\rightarrow Y \quad \text{Cor}(Z, Y | X) = 0$$

Cutoff causes outcome *only through* program? Yep.

Exogenous?

$$U \not\rightarrow Z \quad \text{Cor}(Z, U) = 0$$

Unobserved things that influence outcome don't also influence cutoff?  
It's an arbitrary cutoff, so sure.

# Doubly local LATE

**Effect is only for  
(1) compliers (2) near the cutoff**

**Be specific when talking about effects;  
definitely don't make population-level claims**

# Parametric fuzzy RD

## Step 1: Center running variable + make threshold variable

```
tutoring_centered <- tutoring %>%  
  mutate(entrance_centered = entrance_exam - 70,  
         below_cutoff = entrance_exam <= 70)  
head(tutoring_centered, 6)
```

```
## # A tibble: 6 × 6  
##   id entrance_exam tutoring exit_exam entrance_centered below_cutoff  
##   <int>      <dbl> <lgl>      <dbl>      <dbl> <lgl>  
## 1     1      92.4 FALSE      78.1      22.4  FALSE  
## 2     2      72.8 FALSE      58.2       2.77  FALSE  
## 3     3      53.7  TRUE      62.0     -16.3  TRUE  
## 4     4      98.3 FALSE      67.5      28.3  FALSE  
## 5     5      69.7  TRUE      54.1     -0.288 TRUE  
## 6     6      68.1  TRUE      60.1     -1.93  TRUE
```



# Parametric fuzzy RD

## Step 2: Use cutoff as instrument in 2SLS model

```
# Bandwidth ± 10
fuzzy1 <- iv_robust(
  exit_exam ~ entrance_centered + tutoring | entrance_centered + below_cutoff,
  data = filter(tutoring_centered, entrance_centered >= -10 & entrance_centered <= 10)
)

tidy(fuzzy1)
```

##		term	estimate	std.error	statistic	p.value
## 1		(Intercept)	60.1413558	1.01765573	59.097939	9.746624e-200
## 2		entrance_centered	0.4366281	0.09929619	4.397229	1.407213e-05
## 3		tutoringTRUE	9.7410444	1.91184891	5.095091	5.384163e-07

# Nonparametric fuzzy RD

Use the `fuzzy` argument in `rdrobust()`

**Important! Specify actual treatment status, *not* the instrument of above/below the cutoff**

```
rdrobust(y = tutoring$exit_exam, x = tutoring$entrance_exam,  
         c = 70, fuzzy = tutoring$tutoring) %>%  
summary()
```

```
## First-stage estimates.
```

```
##
```

```
## =====
```

```
##           Method      Coef. Std. Err.          z      P>|z|      [ 95% C.I. ]
```

```
## =====
```

```
## Conventional      -0.708      0.073     -9.751      0.000     [-0.850 , -0.565]
```