

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

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

δ (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

$$ATE = E(Y_1 - Y_0) = E(Y_1) - E(Y_0)$$

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

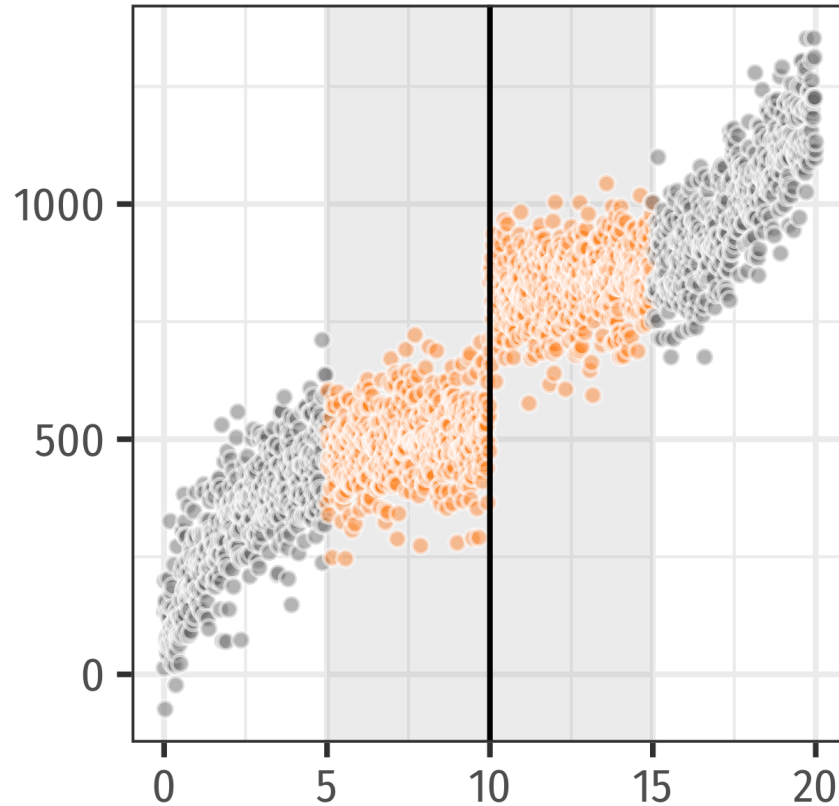
ATT/TOT

Conditional average treatment effect

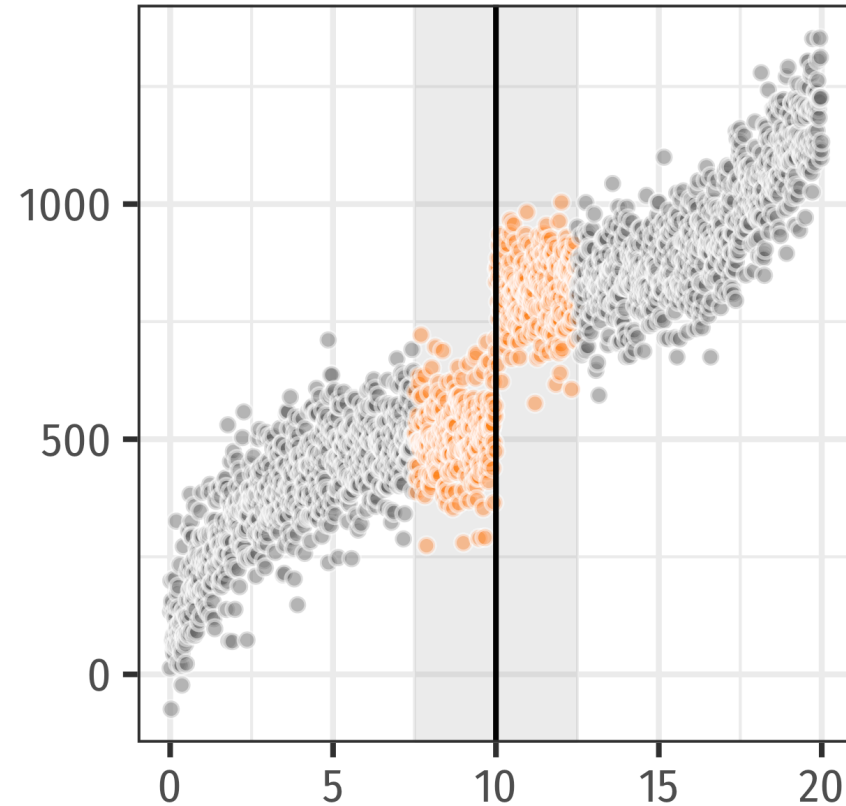
CATE

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**

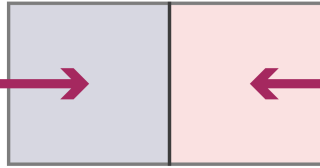
Never taker

**Rejects treatment
regardless of assignment**

Defier

**Does the opposite
of assignment**

Choice if assigned to treatment



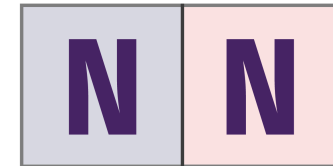
Choice if assigned to control



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**

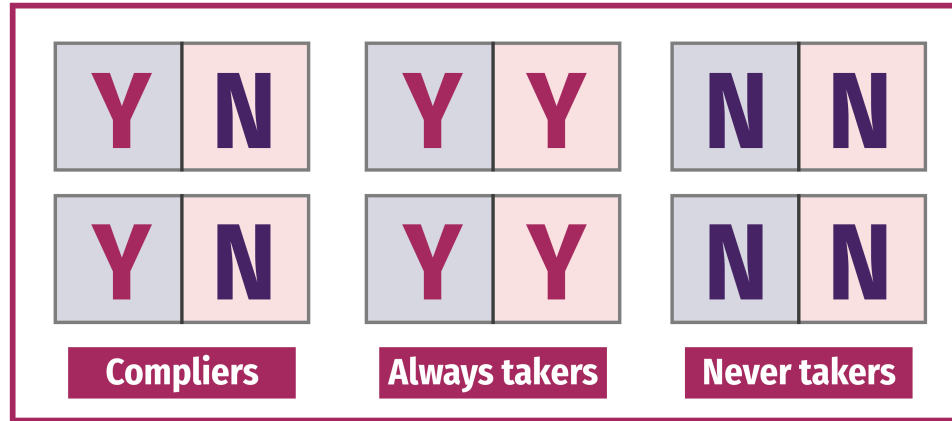
Ignoring defiers

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

**Compliers +
always takers**



Never takers



Assigned to control

Always takers



**Compliers +
never takers**



More causal effects

Intent to treat (ITT)

Effect of assignment (not actual treatment!)

Assigned to treatment

Compliers +
always takers

Y

Never takers

N

Assigned to control

Always takers

Y

Compliers +
never takers

N

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



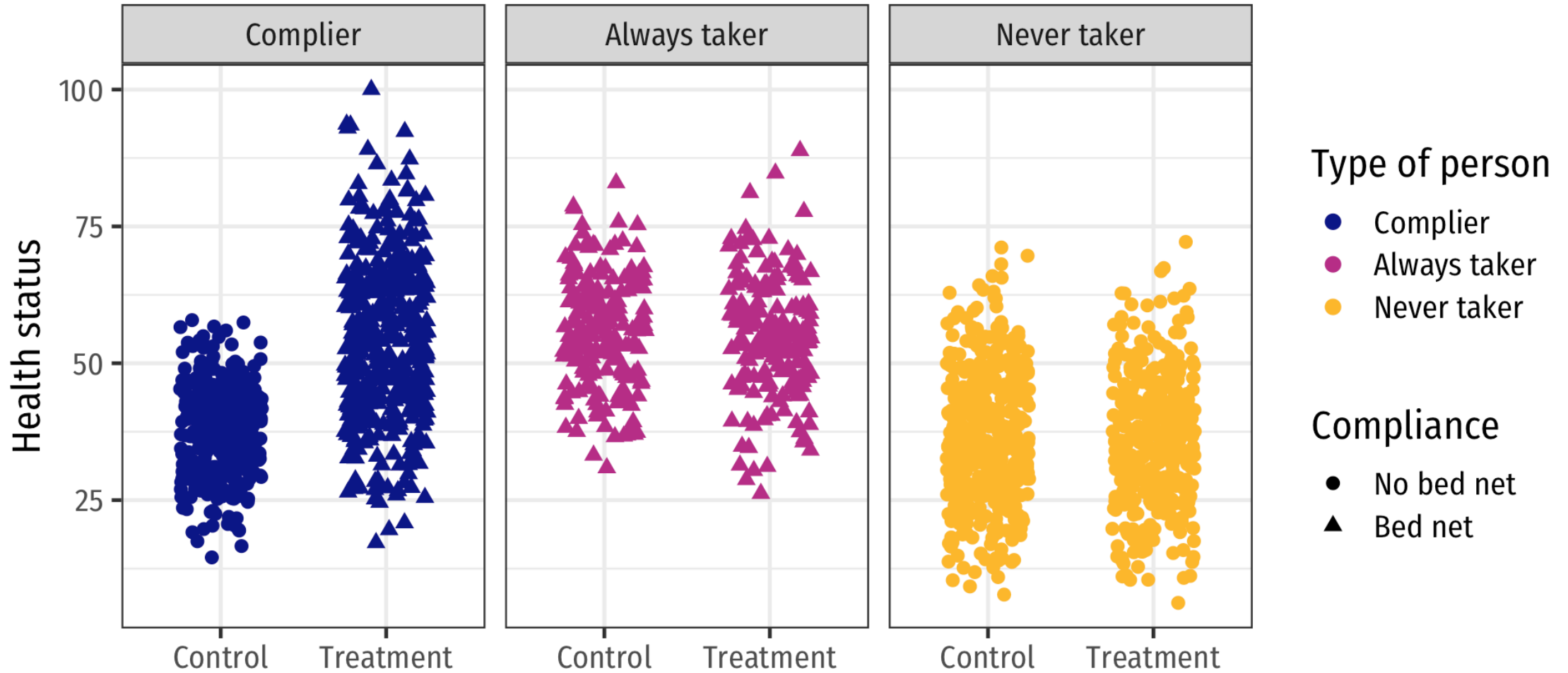
Compliers +
never takers

Hypothetical bed net program

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

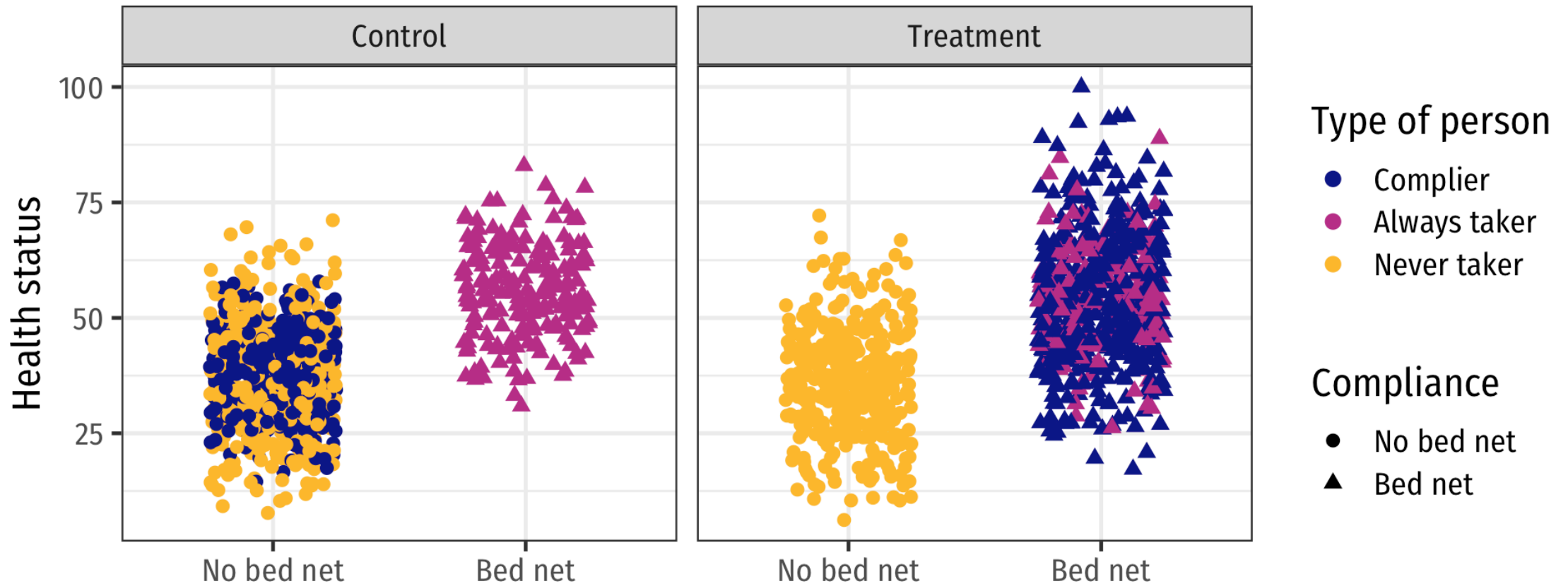
We can read everyone's minds and we know if people are always takers, never takers, or compliers

Mind reading



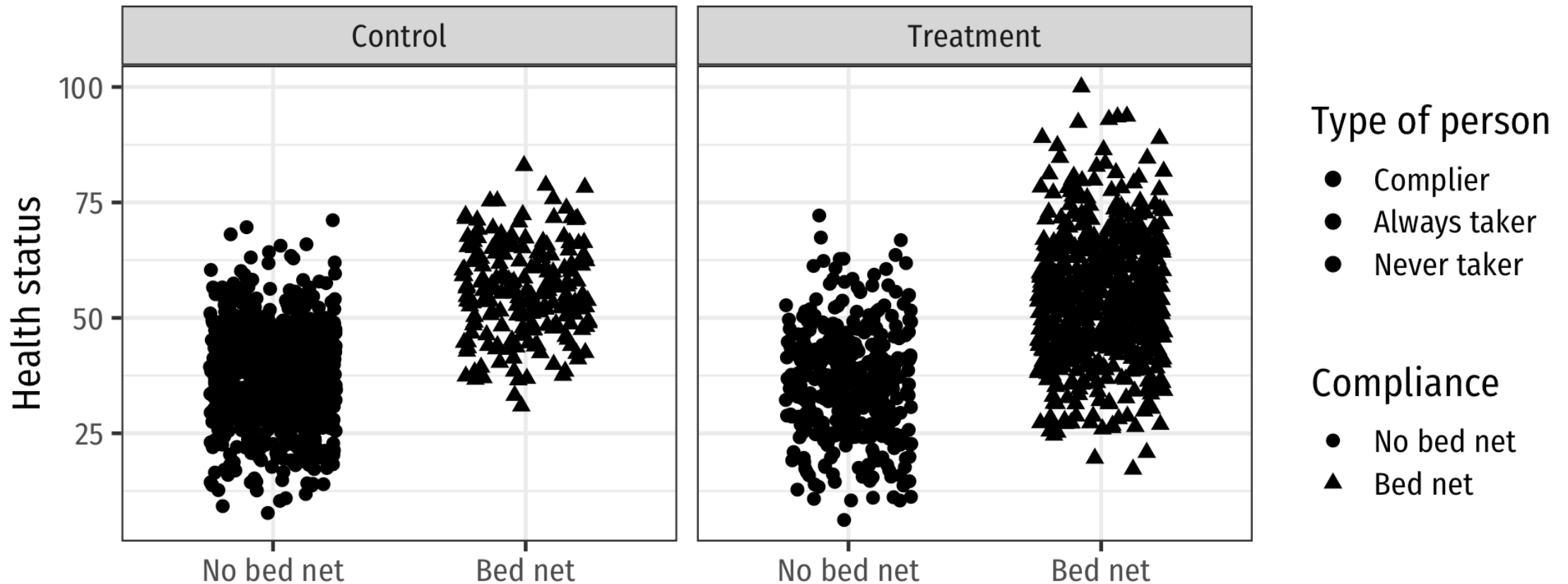
Actual data

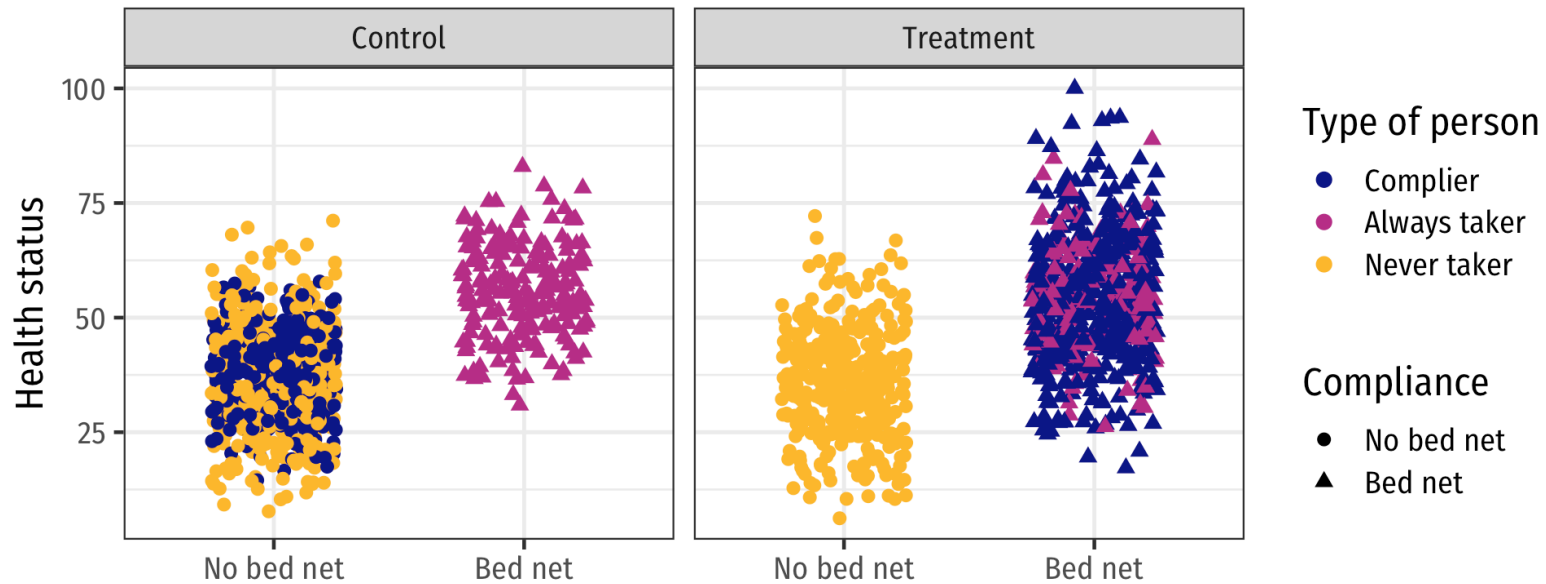
But we can't read minds! This is what we actually see:



Actual data

(Actually *this* is what we see)



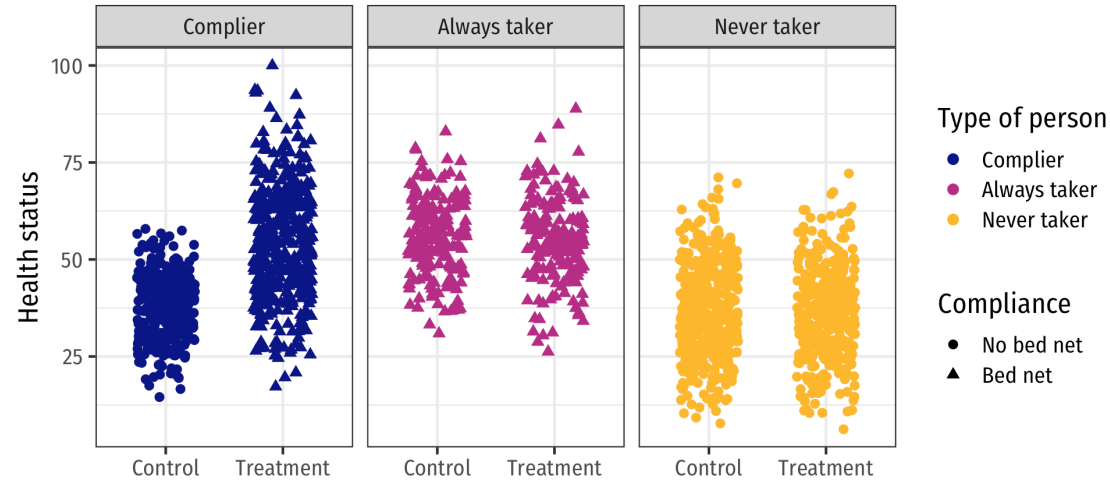


Assigned to control



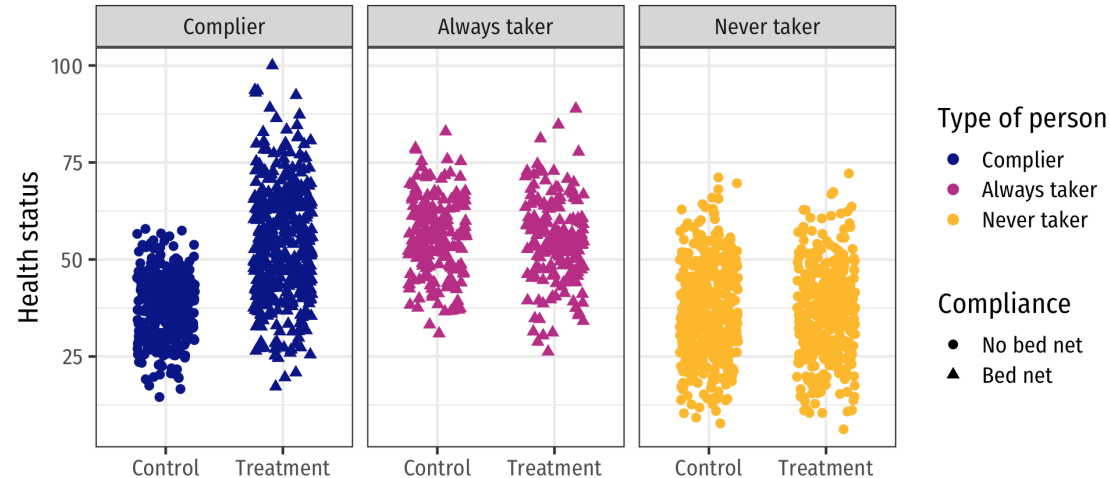
Assigned to treatment





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

$$\text{ITT} = \pi_{\text{C}} \text{CACE} + \pi_{\text{A}} \text{ATACE} + \pi_{\text{N}} \text{NTACE}$$



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

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

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

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

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

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

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

ITT and π_C are both findable!

Finding the ITT

ITT = effect of assignment to treatment on outcome

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

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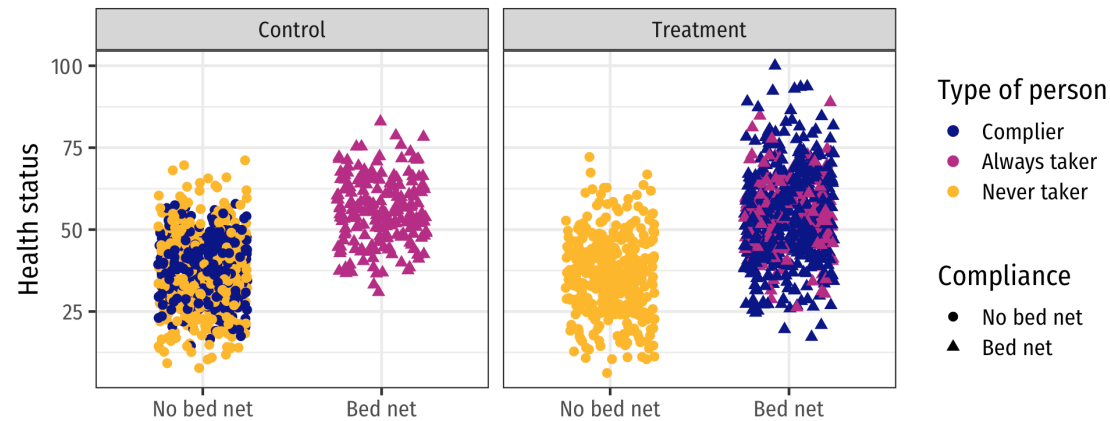
```
bed_nets |>
  group_by(treatment) |>
  summarize(avg = mean(health))
```

```
## [38;5;246m# A tibble: 2 × 2 [39m
```

```
##   treatment    avg
```

Finding the π_C

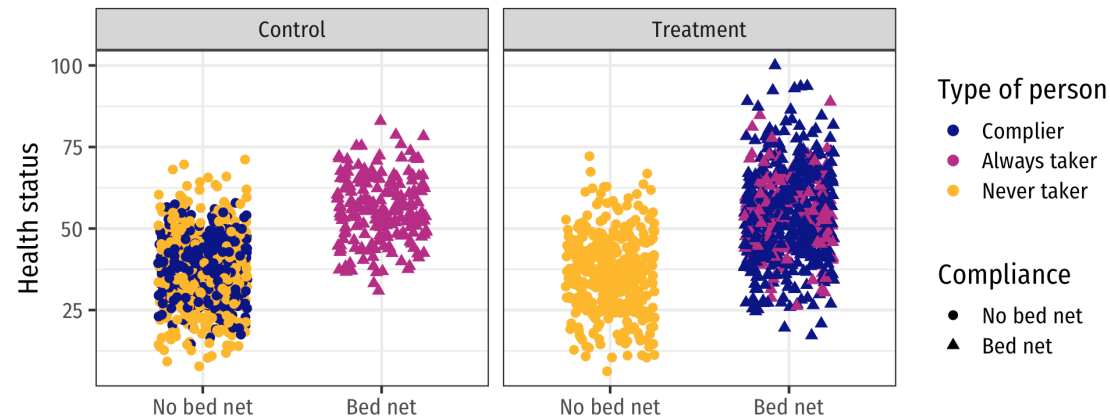
People in treatment group who complied are a combination of Always Takers and Compliers



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

Can we know π_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 π_A !

Isolating π_C

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

`.pull-left.small-code.small[`

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

```
## [38;5;246m# A tibble: 4 × 4 [39m
```

```
## [38;5;246m# Groups:   treatment [2] [39m
```

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_net	Bed 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?

$$U \nrightarrow Z \quad \text{Cor}(Z, U) = 0$$

**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

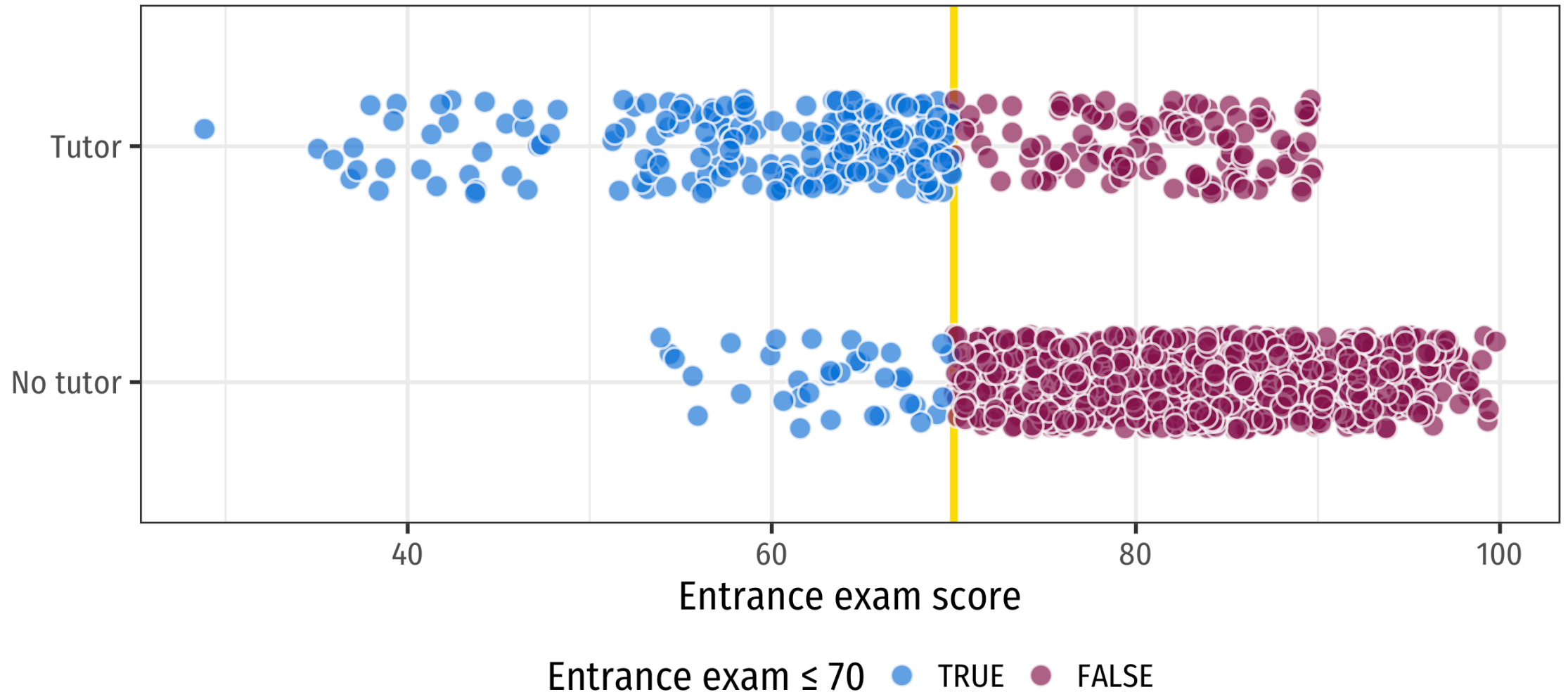
```
iv_robust(outcome ~ program | promotion)
```

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



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?

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

Cutoff causes outcome
only through program? Yep.

Exogenous?

$$U \nrightarrow Z \quad \text{Cor}(Z, U) = 0$$

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

.small-code[

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

```
## [38;5;246m# A tibble: 6 × 6 [39m
```

```
##       id entrance_exam tutoring exit_exam entrance_centered bel
```

```
## [3m [38;5;246m<int> [39m [23m [3m [38;5;246m<dbl> [39m
```

```
## [38;5;250m1 [39m 1 92 4 FALSE 78 1
```


Parametric fuzzy RD

Step 2: Use cutoff as instrument in 2SLS model

```
# Bandwidth  $\pm 10$ 
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.
```

```
##
```

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

```
##           Point      Robust Inference
```

```
##           Estimate          z      P>|z|      [ 95% C.I. ]
```

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