

Randomization & matching

February 26, 2020

PMAP 8521: Program Evaluation for Public Service
Andrew Young School of Policy Studies
Spring 2020

*Fill out your reading report
on iCollege!*

Plan for today

The magic of randomization

The “Gold” Standard

Matching

The magic of randomization

Why randomize?

Fundamental problem of causal inference

$$\delta_i = Y_i^1 - Y_i^0$$

Individual-level effects are
impossible to observe

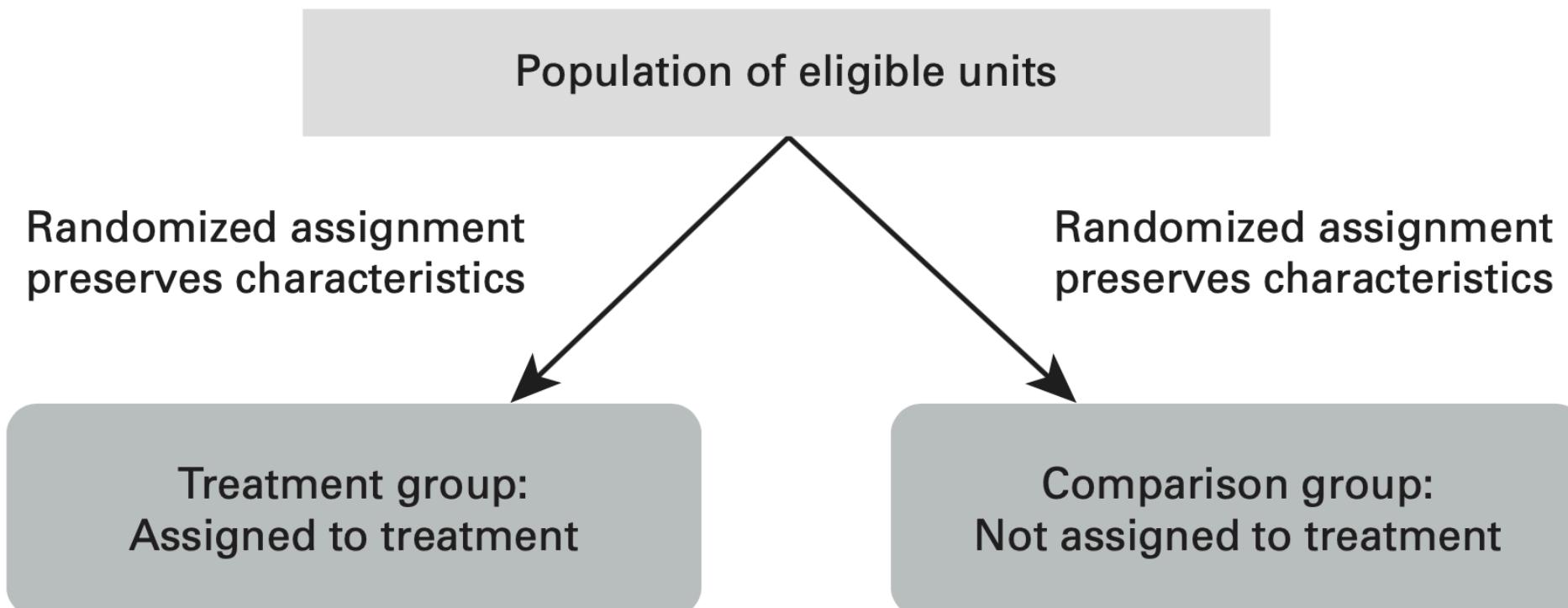
Why randomize?

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

**This only works if subgroups
that received/didn't receive
treatment look the same**

Why randomize?

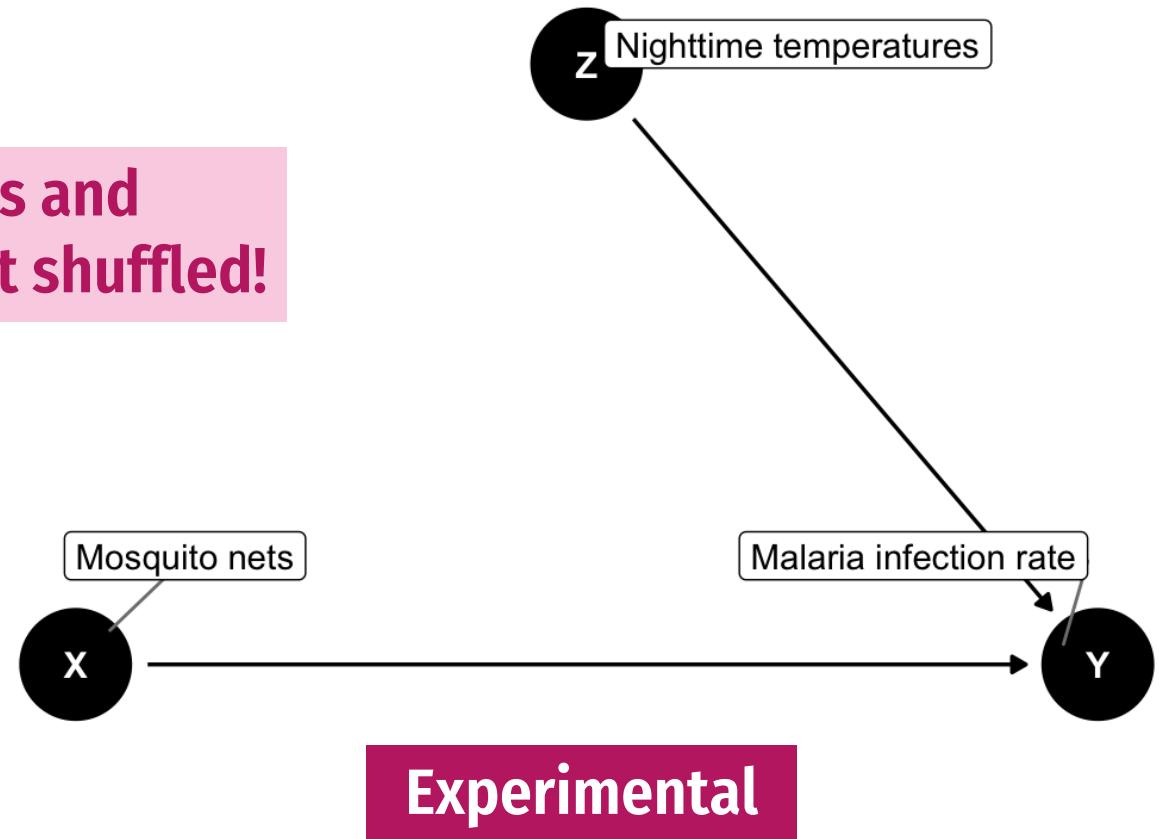
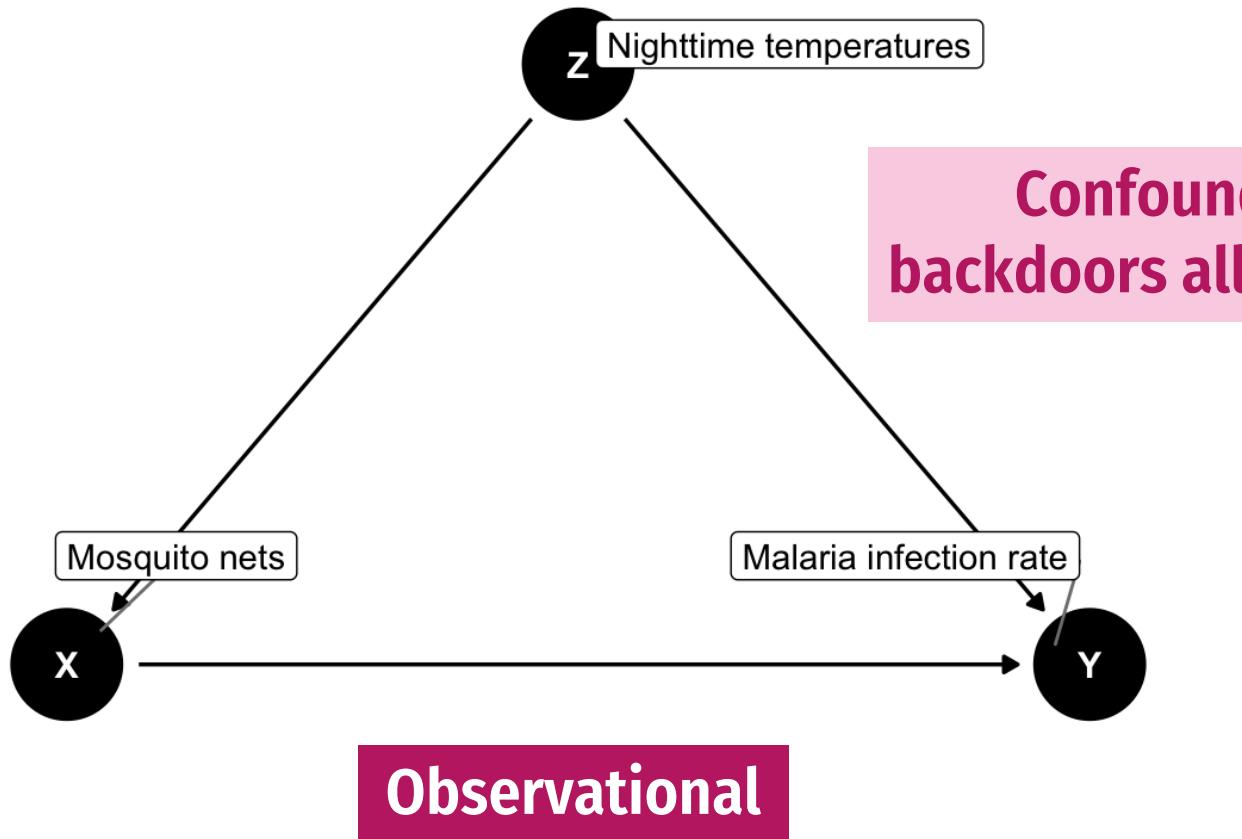
With big enough numbers, the magic of randomization helps make comparison groups comparable



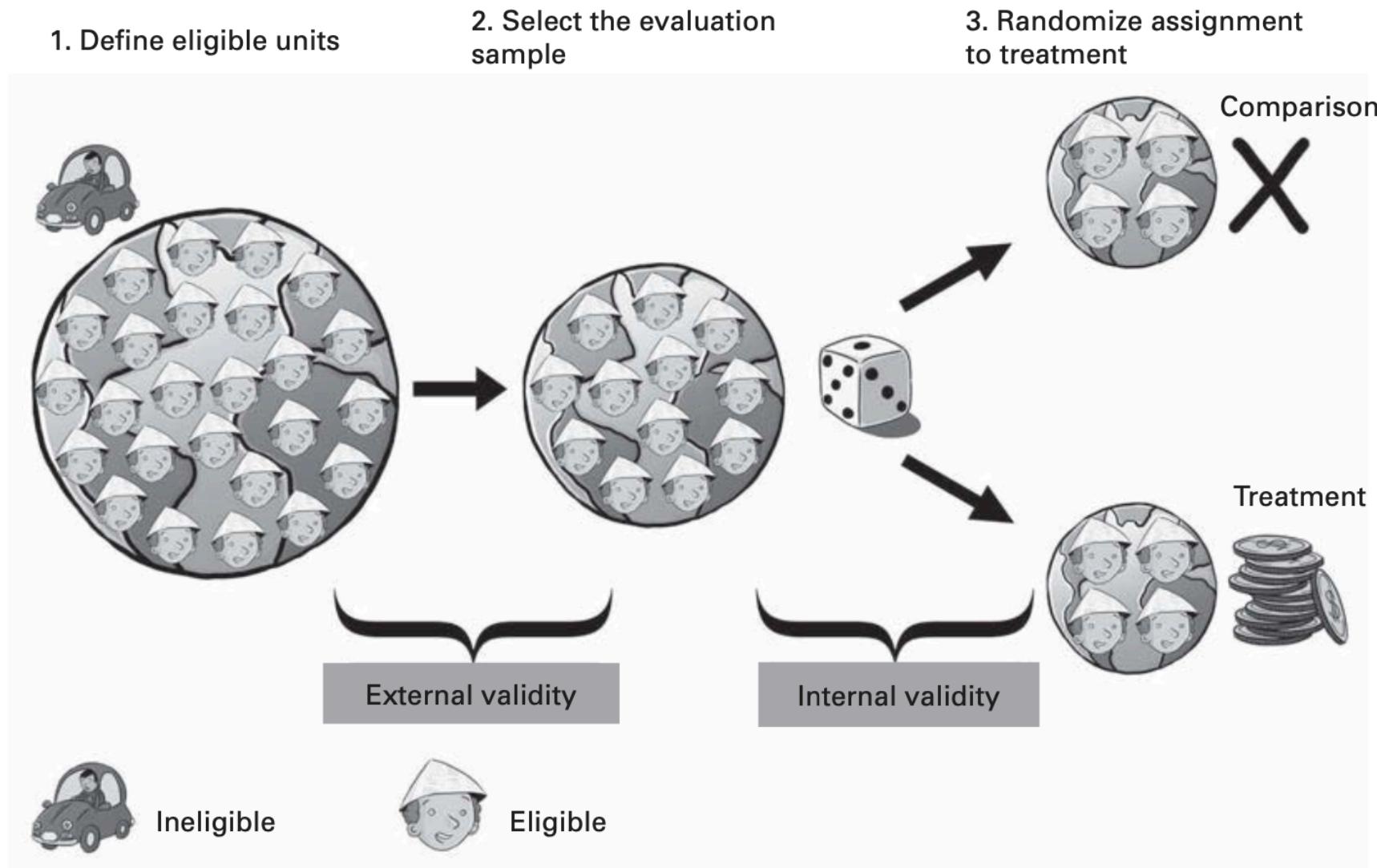
RCTs and DAGs

$P(\text{Malaria infection rate} \mid \text{do}(\text{Mosquito net}))$

When you $\text{do}()$ X, remove all arrows into it



How to randomize?



Random assignment

Coins

Dice

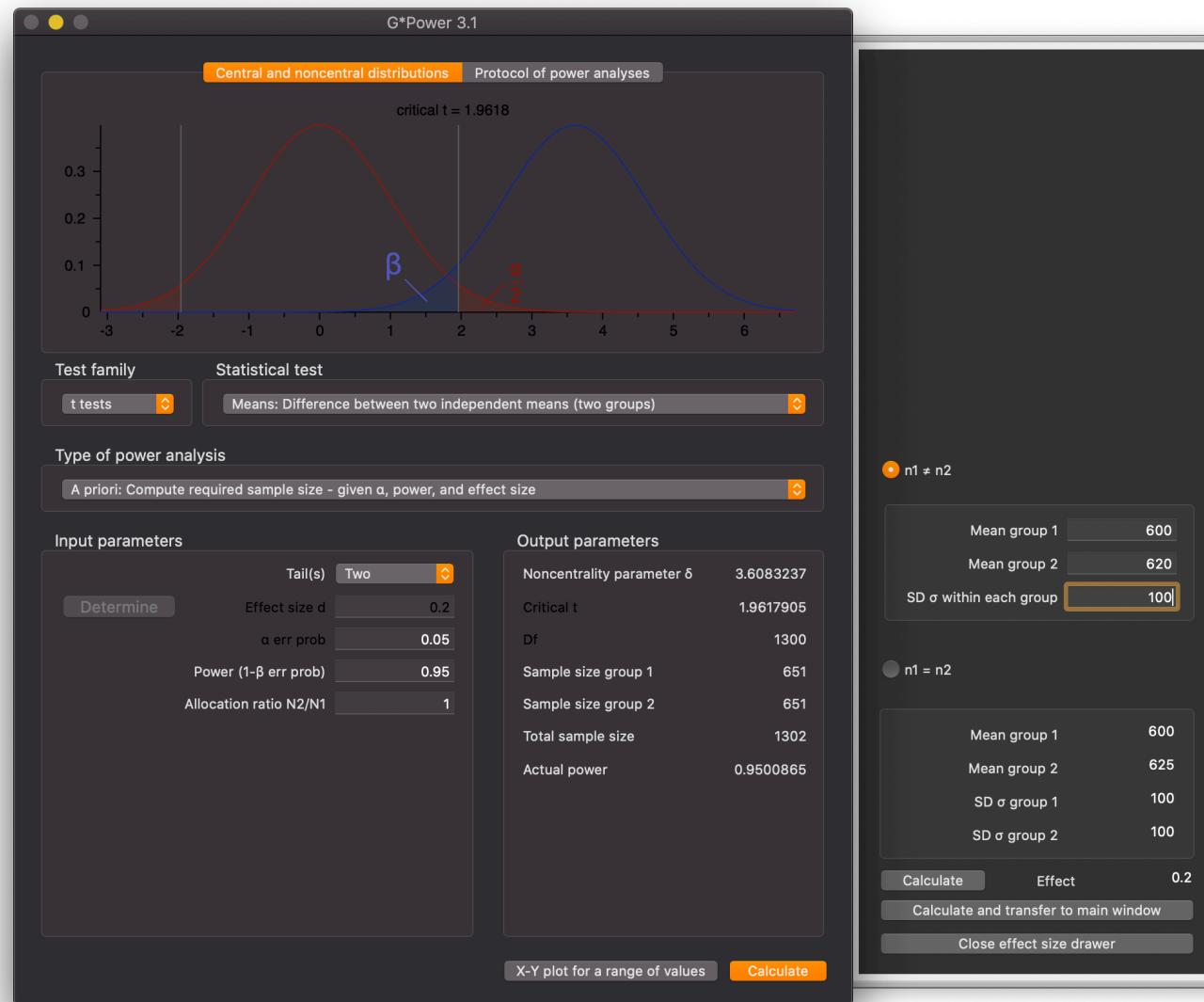
Unbiased lottery

Random numbers + threshold

Atmospheric noise

random.org

How big of a sample?



R example

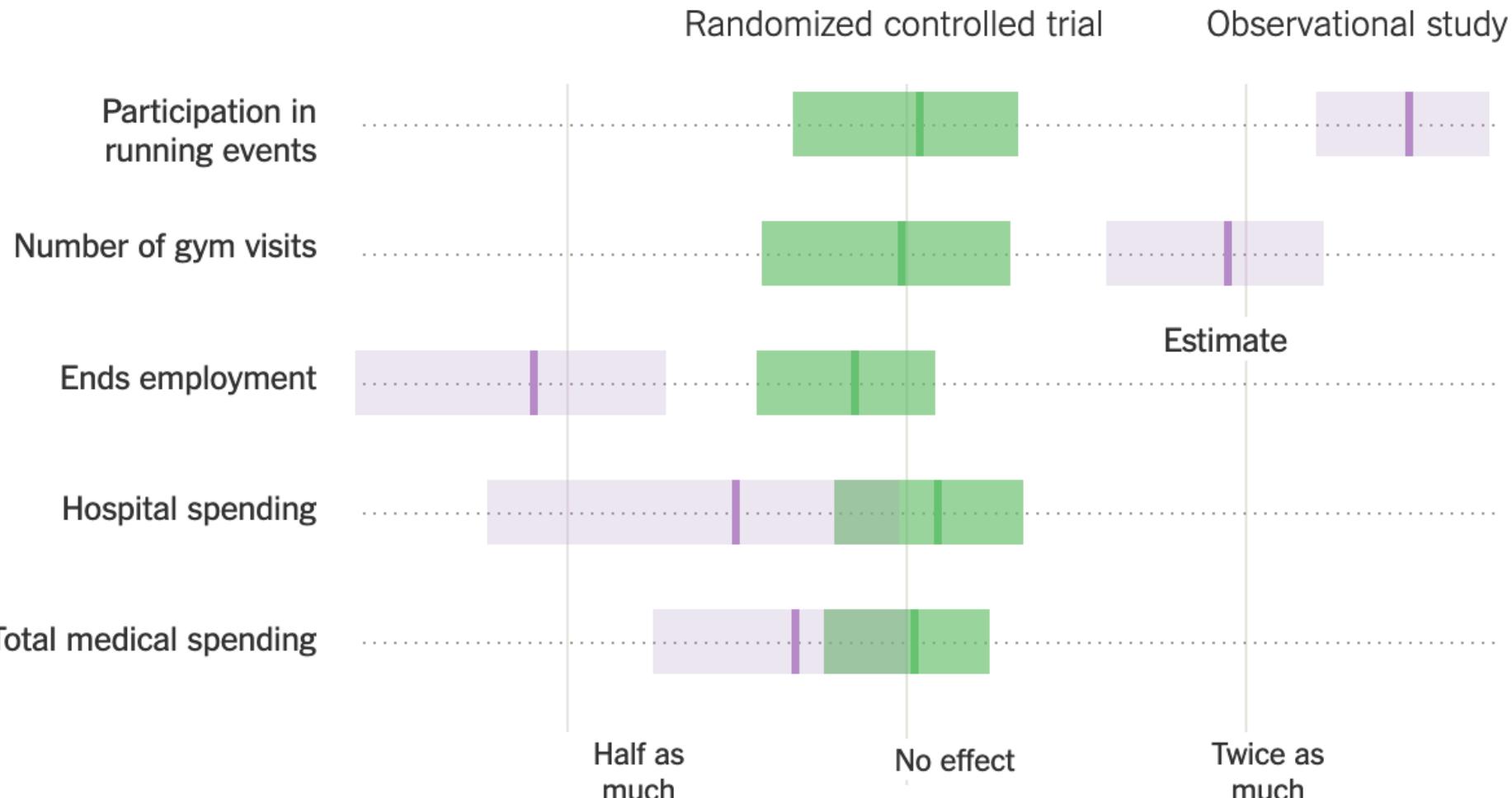
The “Gold” Standard

Types of research

**Experimental studies vs.
observational studies**

Which is better?

How the Illinois Wellness Program Affected ...



Source: What Do Workplace Wellness Programs Do? Evidence from the Illinois Workplace Wellness Study

[BJOG](#). Author manuscript; available in PMC 2018 Dec 1.

Published in final edited form as:

[BJOG. 2018 Dec; 125\(13\): 1716.](#)

Published online 2018 Jun 19. doi: [10.1111/1471-0528.15199](https://doi.org/10.1111/1471-0528.15199)

Randomised controlled trials—the gold standard for effectiveness research

Eduardo Hariton, MD, MBA¹ and Joseph J. Locascio, PhD²

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The publisher's final edited version of this article is available at [BJOG](#)

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rct "gold standard"

All

Shopping

News

V

About 636,000 results (0.67 seconds)

PMCID: PMC6235704

NIHMSID: NIHMS966617

PMID: [29916205](#)

Randomized Assignment of Treatment

When a program is assigned at random—that is, using a lottery—over a large eligible population, we can generate a robust estimate of the counterfactual. *Randomized assignment of treatment is considered the gold standard of impact evaluation.* It uses a random process, or chance, to decide who is granted access to the program and who is not.¹ Under randomized assignment, every eligible unit (for example, an individual, household, business,

RCTs are great!

Super impractical to do
all the time though!

Business



3 share Nobel Prize in economics for ‘experimental approach’ to solving poverty

Esther Duflo, who at 46 is the award's youngest winner, shares the honor with fellow MIT economist Abhijit Banerjee and Harvard's Michael Kremer.



Massachusetts Institute of Technology (MIT) @MIT · 5h Professors Esther Duflo and Abhijit Banerjee, co-directors of MIT's @JPAL, receive congratulations on the big news this morning. They share in the #NobelPrize in economic sciences "for their experimental approach to alleviating global poverty."

Photo: Bryce Vickmark





Grad School Imposter @darinself · 6h

Siri, can you sum up the issues of gender and Economics in one headline???



Rohini Mohan ✅ @rohini_mohan · 7h

Oh COME ON @EconomicTimes!

Business News > News > Politics and Nation > Indian-American MIT Prof Abhijit Banerjee and wife wins Nobel in Economics

Benchmarks >

Sensex • CLOSED

38,214.47 ↑ 87.39



NSE Loser-Large Cap >

Infosys

786.10 ↓ -28.70



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Axis Long Term
Plan-Growth



Indian-American MIT Prof Abhijit Banerjee and wife wins Nobel in Economics

Banerjee, born in 1961 in Mumbai, bagged the award for his "experimental approach to alleviating global poverty".

PTI | Updated: Oct 14, 2019, 04.18 PM IST



1
Comments

Save

A+



BCCL

STOCKHOLM: Indian-American Abhijit

“Gold standard”

“Gold standard” implies that all causal inferences will be valid if you do the experiment right

We don't care if studies are experimental or not

We care if our causal inferences are valid

RCTs are a helpful baseline/rubric for other methods

**Moving to
Opportunity**

RCTs and validity

Randomization fixes a ton of internal validity issues

Selection

Treatment and control groups are comparable; people don't self-select

Trends

Maturation, secular trends, seasonality, regression to the mean all generally average out

RCTs and validity

RCTs don't fix attrition!

Worst threat to internal validity in RCTs

If attrition is correlated with treatment, that's bad

People might drop out because of the treatment, or because they got/didn't get the control group

Addressing attrition

Recruit as effectively as possible

You don't just want weird/WEIRD participants

Get people on board

Get participants invested in the experiment

Collect as much baseline information as possible

Check for randomization of attrition

RCTs and validity

Randomization failures

Check baseline pre-data

Noncompliance

**Some people assigned to treatment won't take it;
some people assigned to control will take it**

Intent-to-treat (ITT) vs. Treatment-on-the treated (TTE)

Other limitations

RCTs don't magically fix construct validity
and statistical conclusion validity

RCTs definitely don't
magically fix external validity

The Nobel Prize in economics goes to three groundbreaking antipoverty researchers

In the last 20 years, development economics has been transformed. These researchers are the reason why.

By Kelsey Piper | Oct 14, 2019, 3:30pm EDT

Empiricism and development economics

The transformation of development economics into an intensely empirical field that leans heavily on randomized controlled trials hasn't been uncontroversial, and many of **the responses** to the Nobel Prize announcement acknowledge that controversy.

Critics have **complained that** randomization feels much more scientific than other approaches but doesn't necessarily answer our questions any more definitively. **Others worry** that the focus on small-scale questions — Do wristbands increase vaccination rates? Do textbooks improve school performance? — might distract us from addressing larger, structural contributors to poverty.

When to randomly assign

Demand for treatment exceeds supply

Treatment will be phased in over time

Treatment is in equipoise

Local culture open to randomization

When you're a nondemocratic monopolist

When people won't know (and it's ethical!)

When lotteries are going to happen anyway

When to not randomly assign

When you need immediate results

When it's unethical or illegal

When it's something that happened in the past

When it involves universal ongoing phenomena

Matching

Applicant group	Private				Public				Altered State	1996 earnings
	Student	Ivy	Leafy	Smart	All State	Tall State	State	State		
A	1		Reject	Admit			Admit			110,000
	2		Reject	Admit			Admit			100,000
	3		Reject	Admit			Admit			110,000
B	4	Admit			Admit			Admit	Admit	60,000
	5	Admit			Admit			Admit	Admit	30,000
C	6		Admit							115,000
	7		Admit							75,000
D	8	Reject			Admit	Admit				90,000
	9	Reject			Admit	Admit				60,000

Note: Enrollment decisions are highlighted in gray.

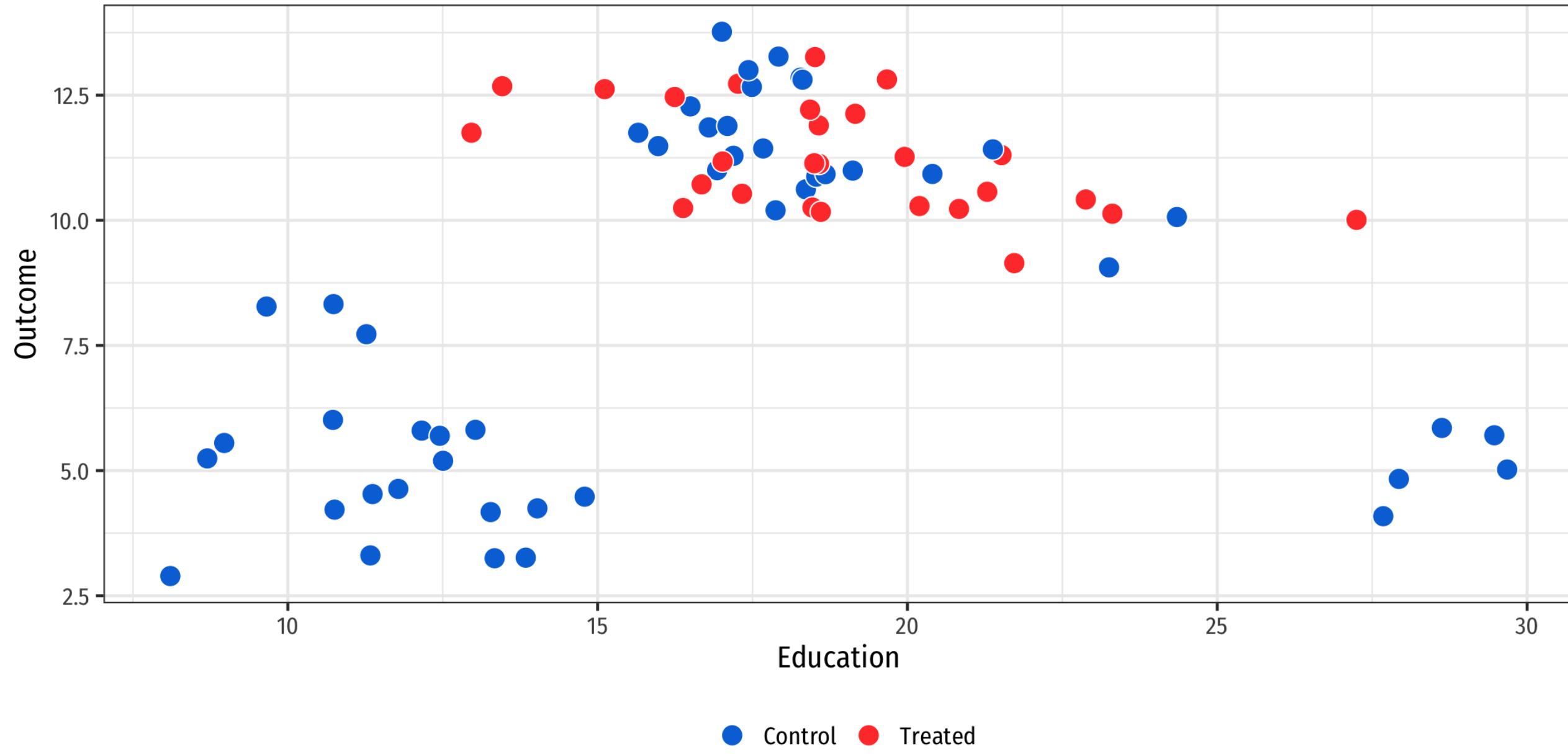
Why match?

Reduce model dependence

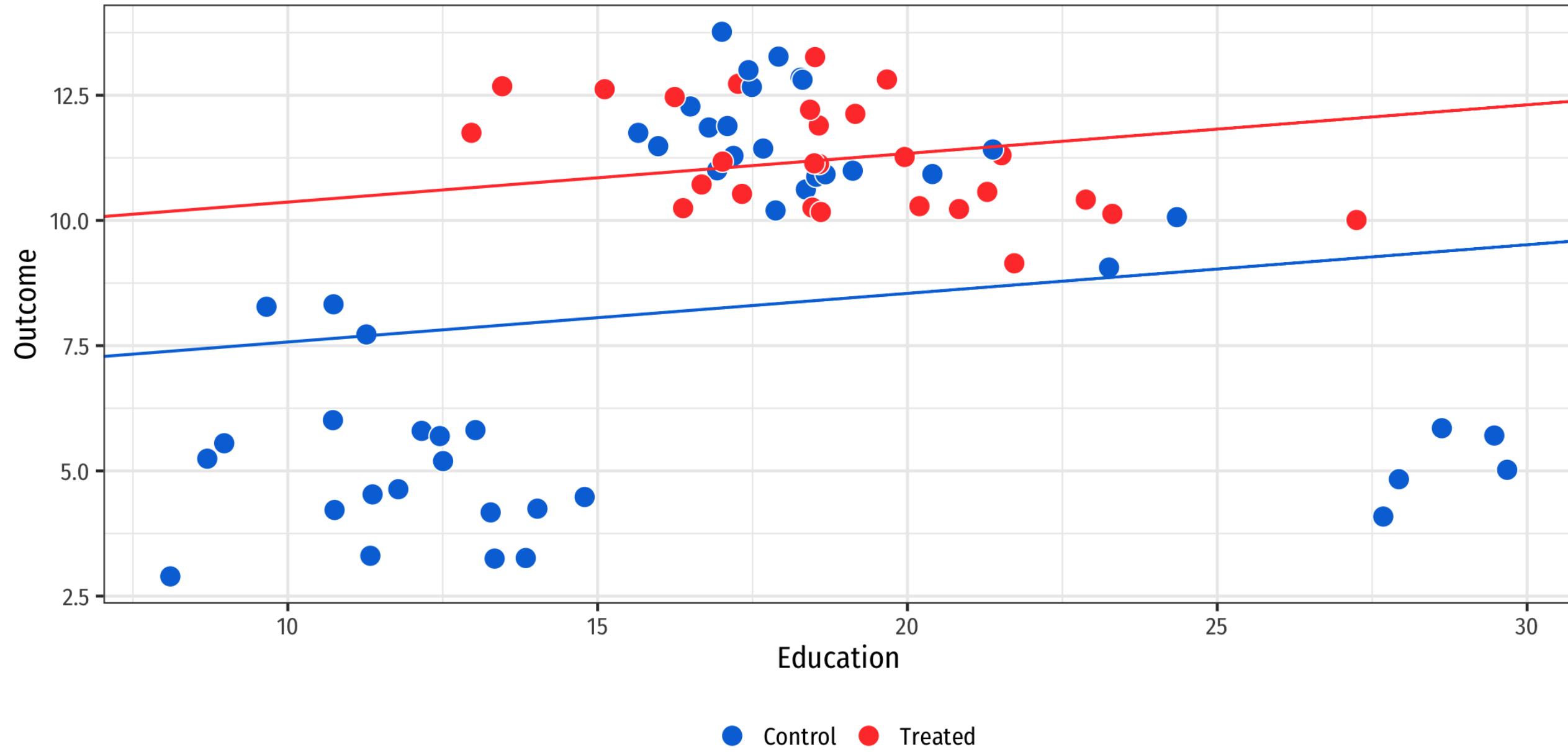
Imbalance → model dependence → researcher discretion → bias

Compare apples to apples

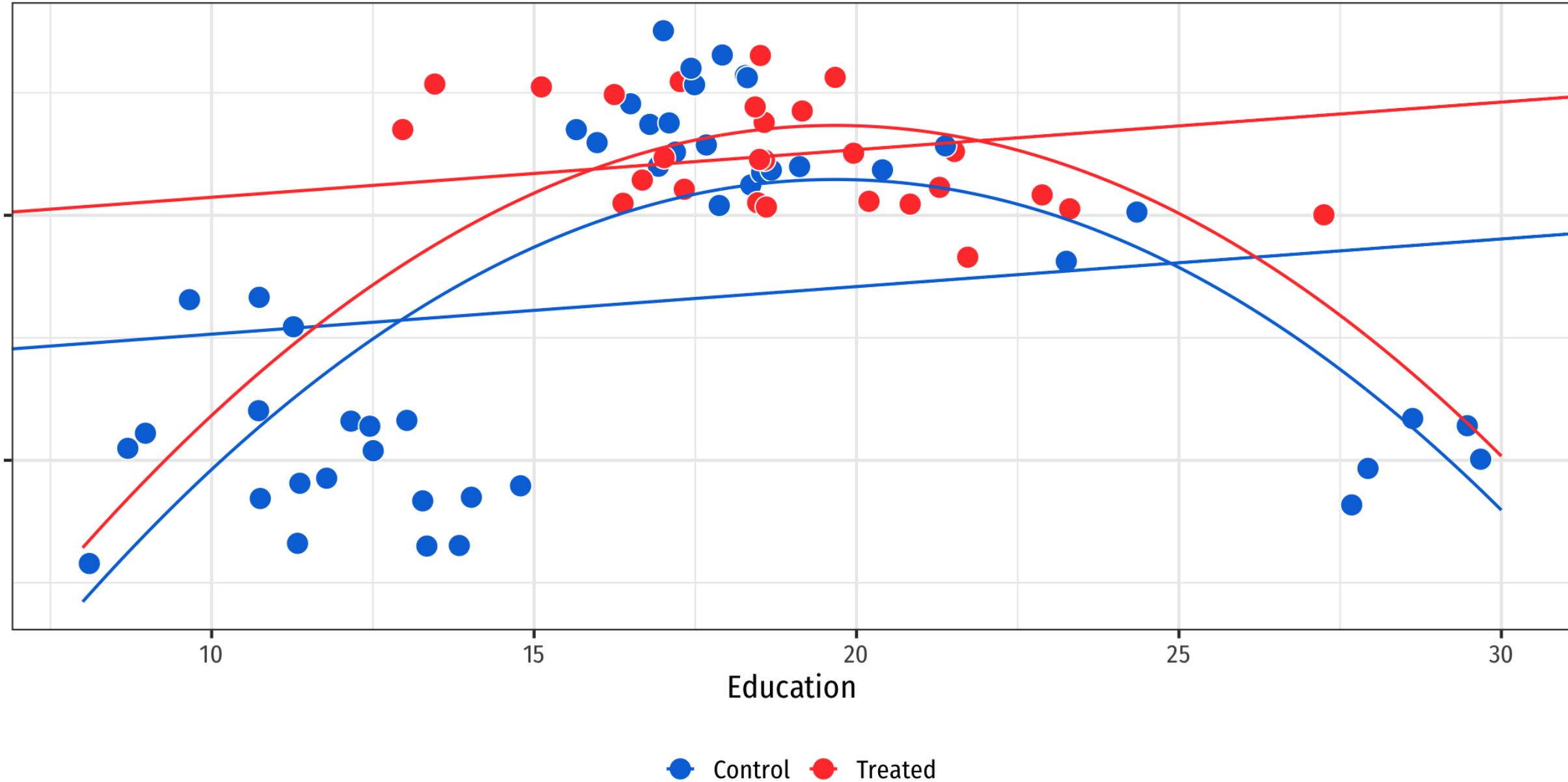
It's a way to adjust for backdoors!

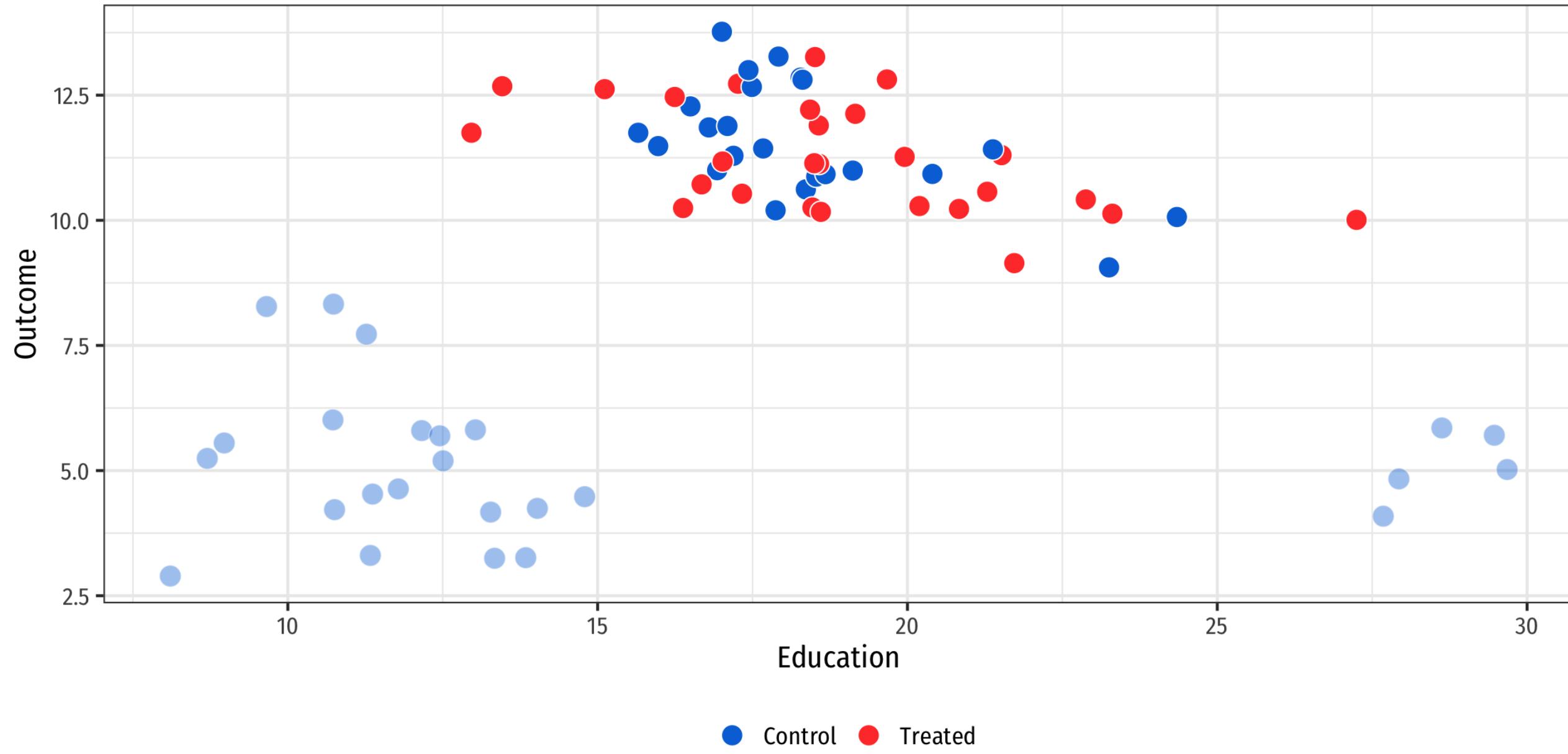


$$\text{Outcome} = \beta_0 + \beta_1 \text{Education} + \beta_2 \text{Treatment}$$

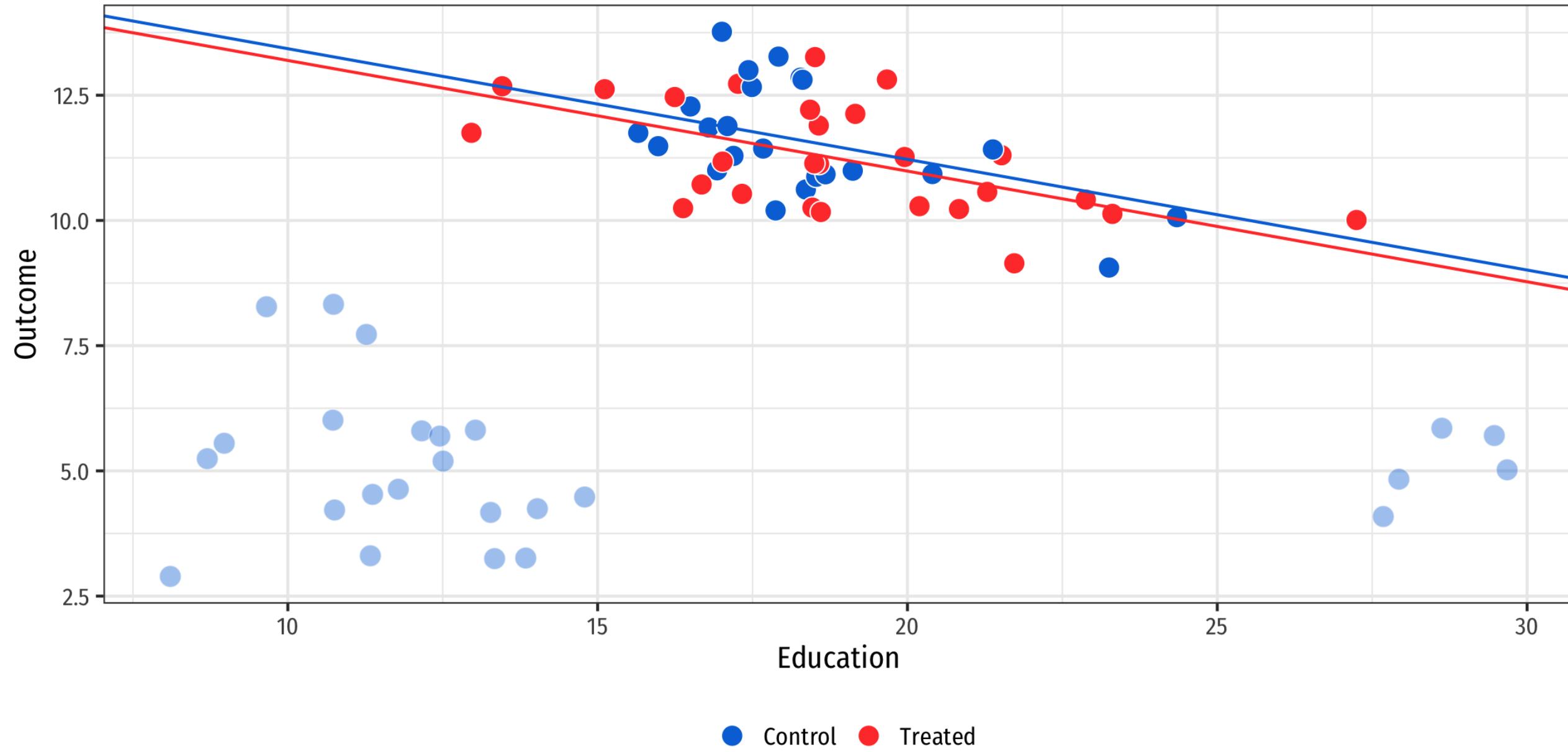


$$\text{Outcome} = \beta_0 + \beta_1 \text{Education} + \beta_2 \text{Education}^2 + \beta_3 \text{Treatment}$$

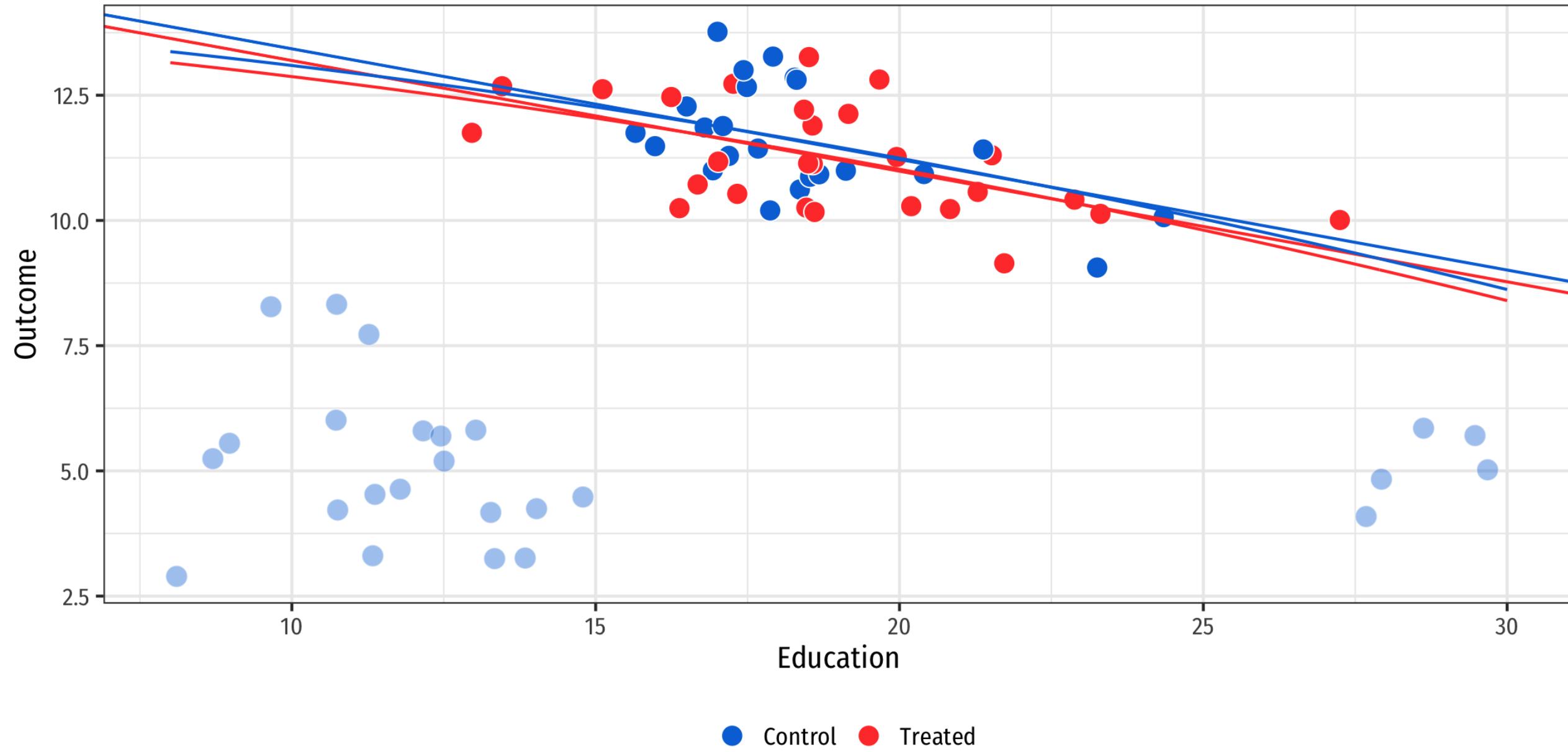


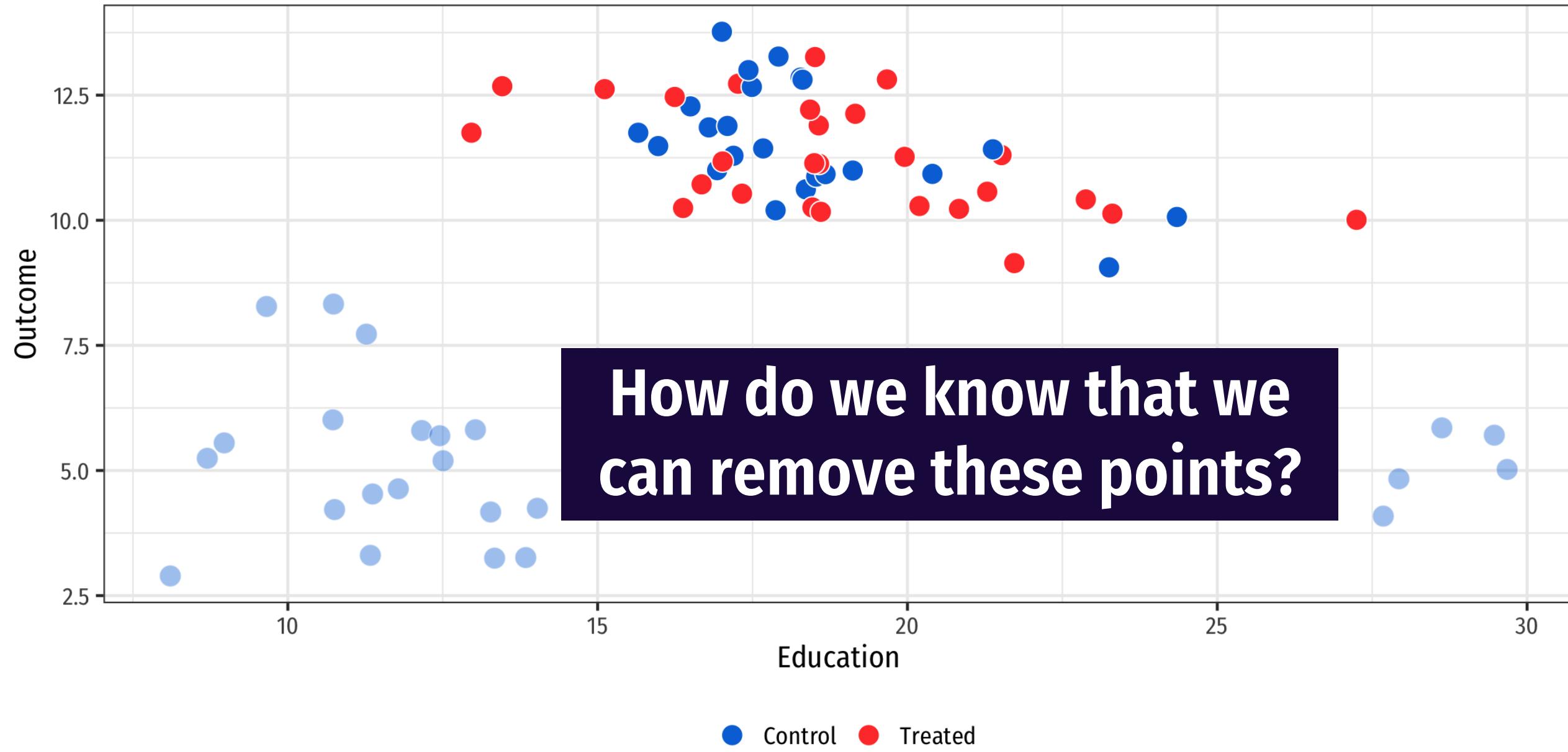


$$\text{Outcome} = \beta_0 + \beta_1 \text{Education} + \beta_2 \text{Treatment}$$



$$\text{Outcome} = \beta_0 + \beta_1 \text{Education} + \beta_2 \text{Education}^2 + \beta_3 \text{Treatment}$$





General process for matching

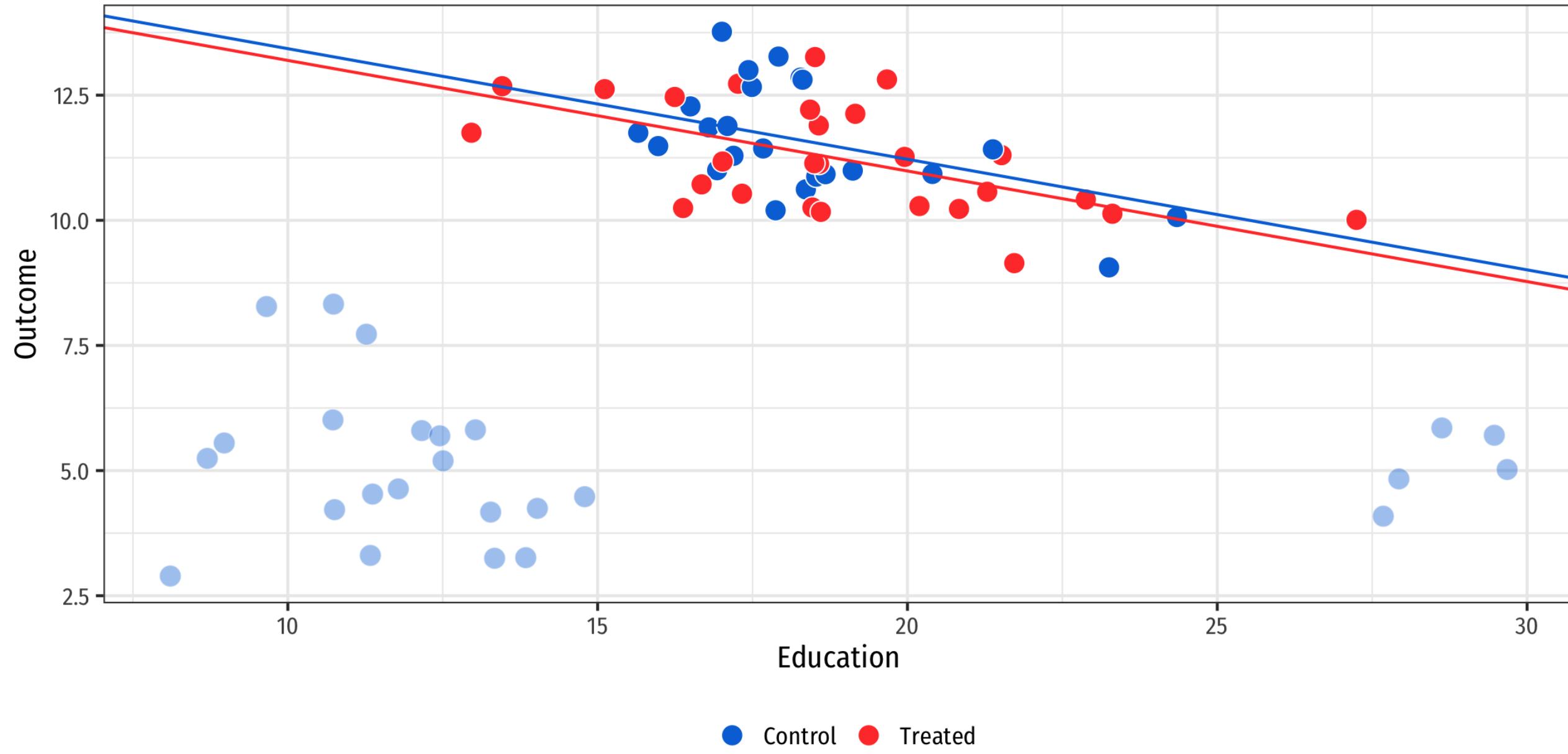
1. Preprocess data

Do something to guess or model the assignment to treatment

Use what you know about the DAG to inform this!

2. Estimation

Use the new trimmed/preprocessed data to build a model, calculate difference in means, etc.



Different methods

Nearest neighbor matching (NN)

Mahalanobis distance / Euclidean distance

Coarsened exact matching (CEM)

Propensity score matching (PSM)

Inverse probability weighting (IPW)

Nearest neighbor matching

Find control observations that are very close/similar to treatment observations based on confounders

Lots of mathy ways to measure distance

Mahalanobis and Euclidean distance are most common

There's a 70% chance of recession in the next six months, new study from MIT and State Street finds

PUBLISHED WED, FEB 5 2020 12:20 PM EST | UPDATED WED, FEB 5 2020 4:13 PM EST



Pippa Stevens
@PIPPASTEVENS13

SHARE

That's just Mahalanobis matching!

KEY POINTS

- A new study from the MIT Sloan School of Management and State Street Associate says there's a 70% chance that a recession will occur in the next six months.
- The researchers used a scientific approach initially developed to measure human skulls to determine how the relationship of four factors compares to prior recessions.
- The index currently stands at 76%. Looking at data back to 1916, the researchers found that once the index topped 70%, the likelihood of a recession rose to 70%.

TRENDING NOW



Coronavirus Brazil travel 'irrelevant'

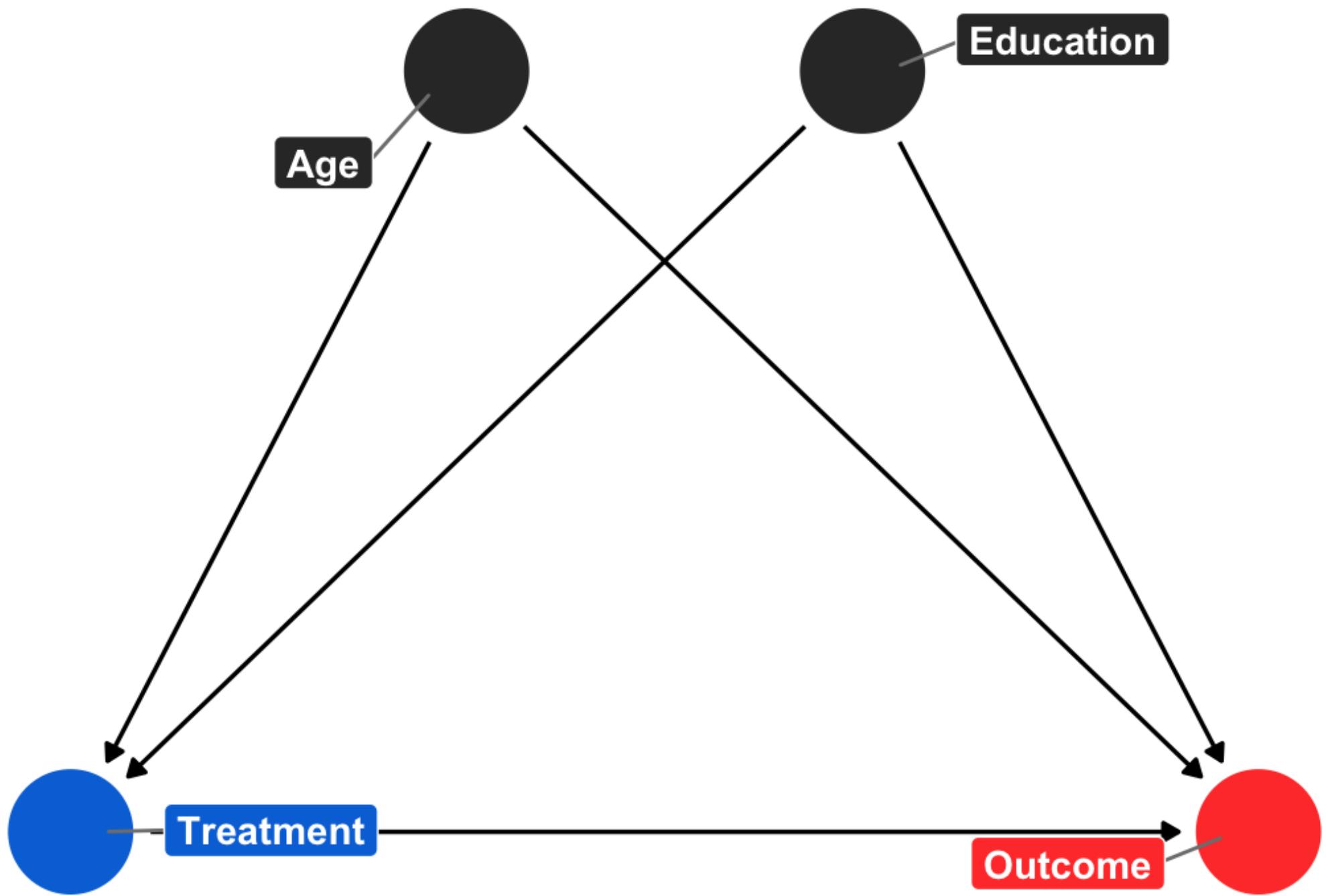


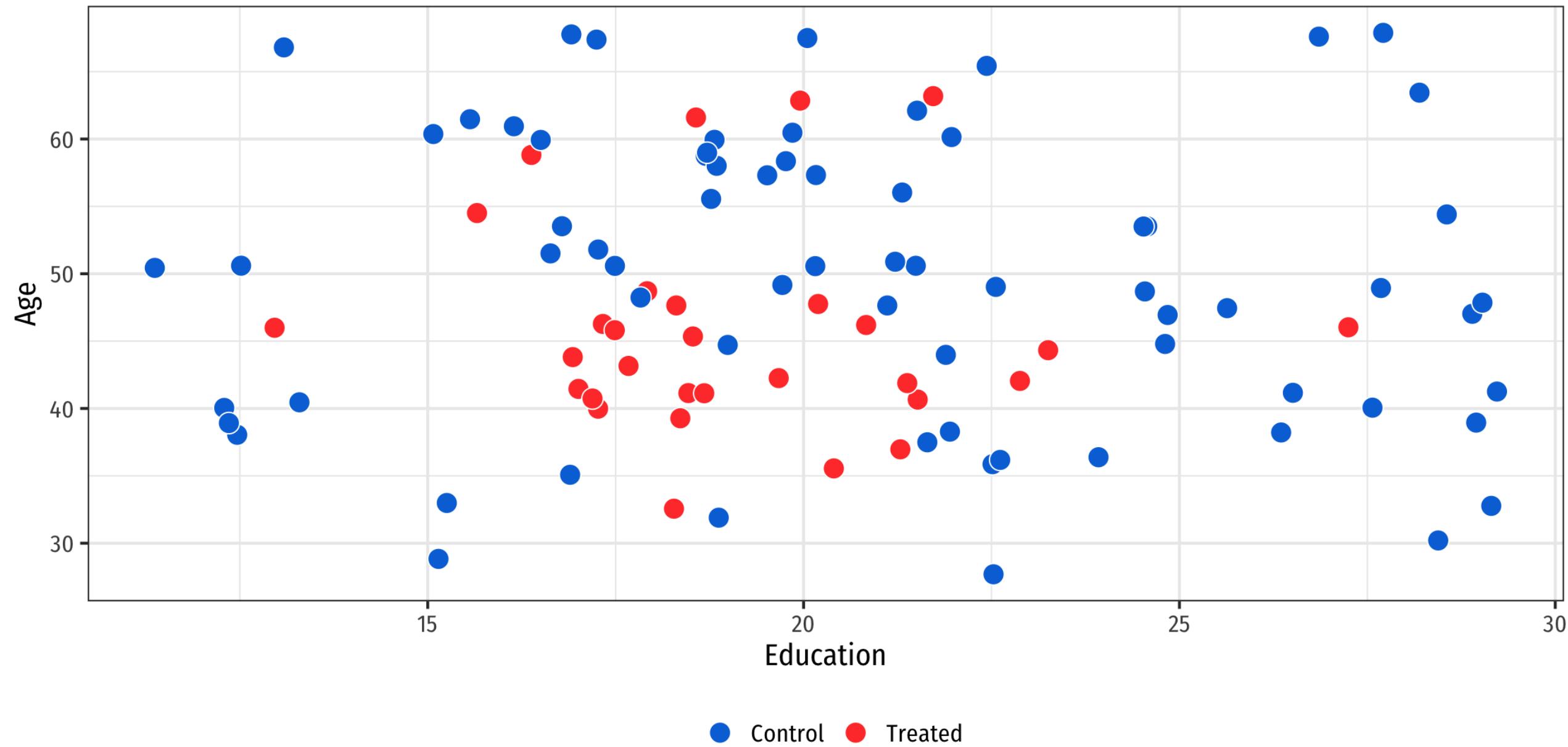
Trump furious markets coron

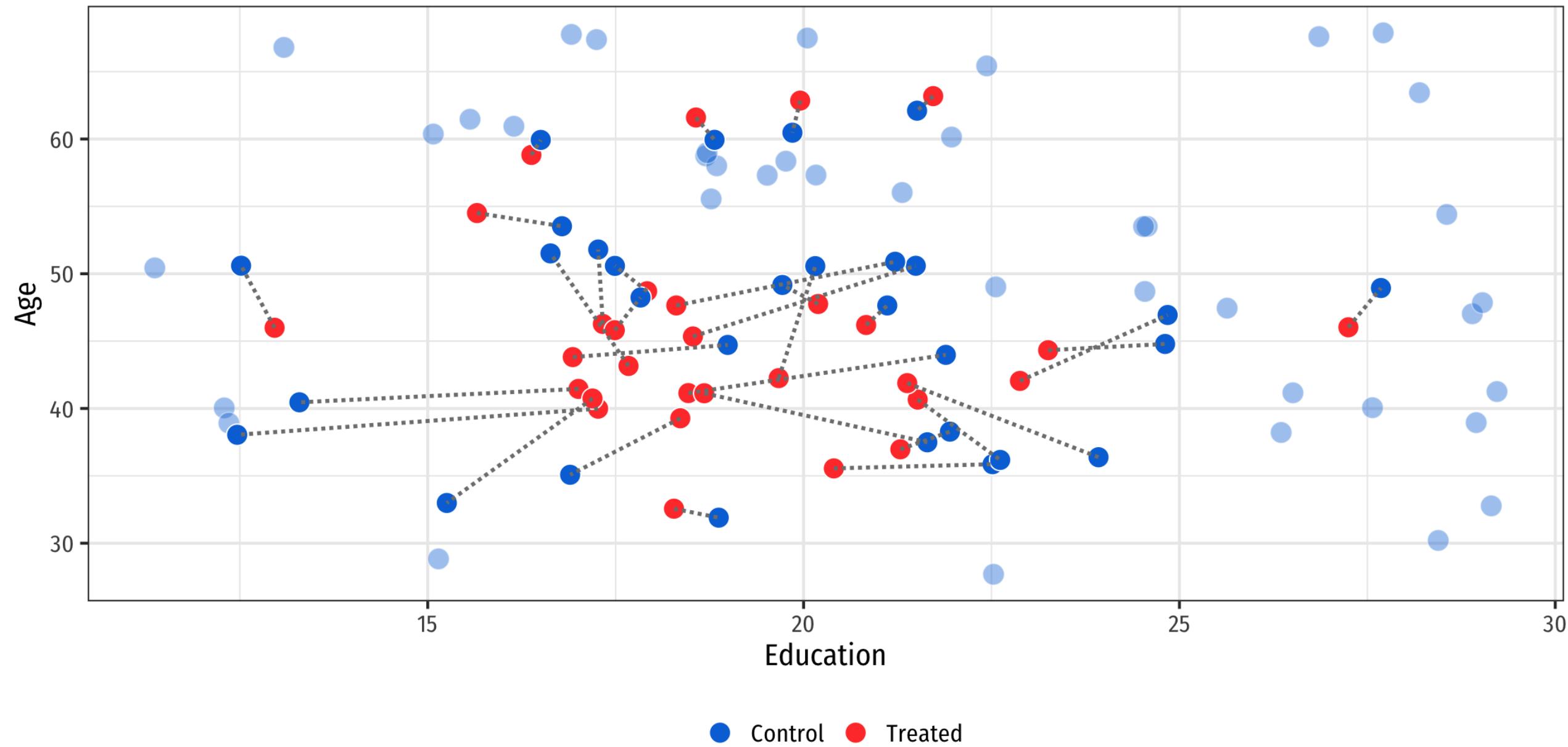
Prasanta Chandra Mahalanobis

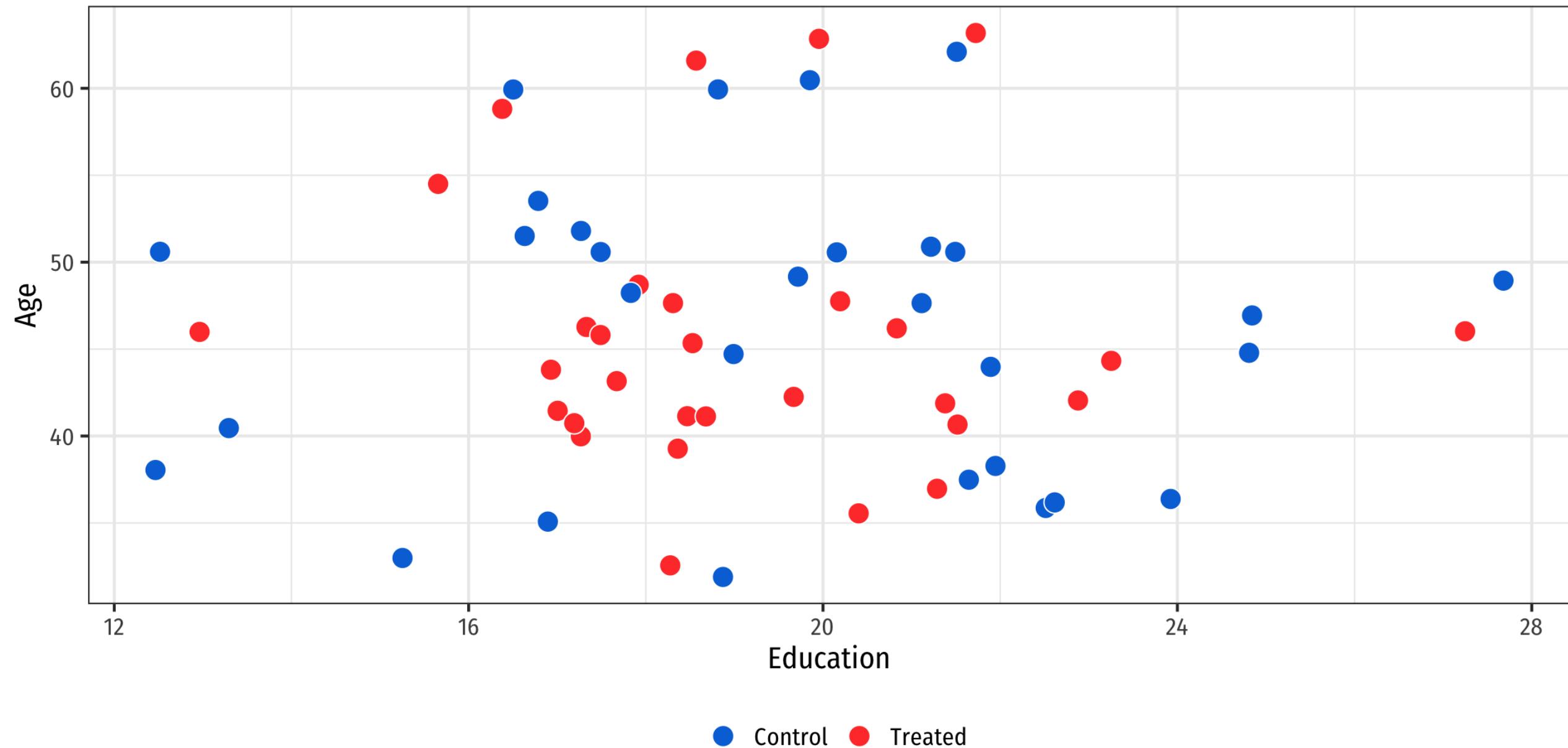


Tried to prove
brain size
differences
between castes;
low-key
eugenicist









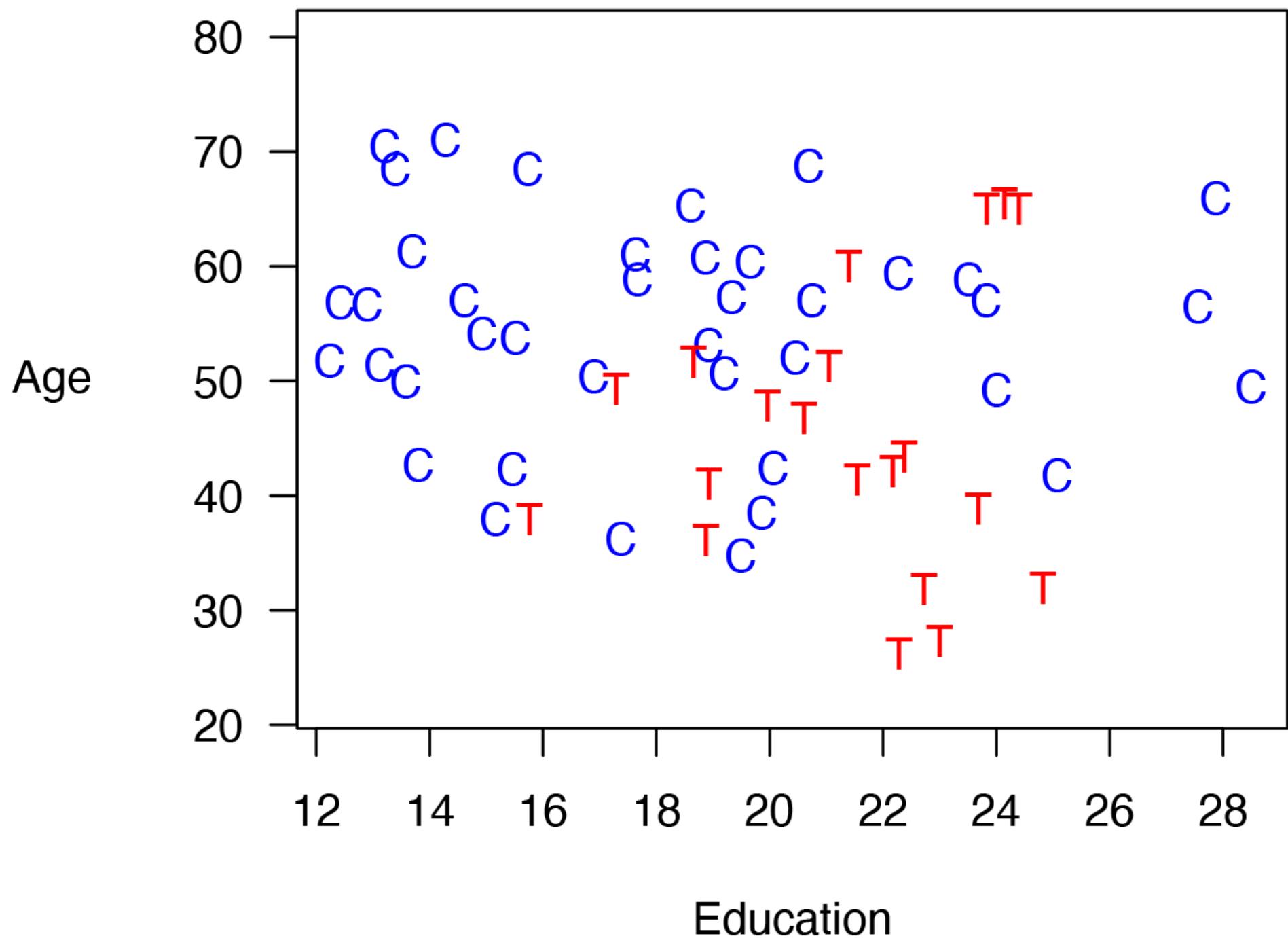
Coarsened exact matching

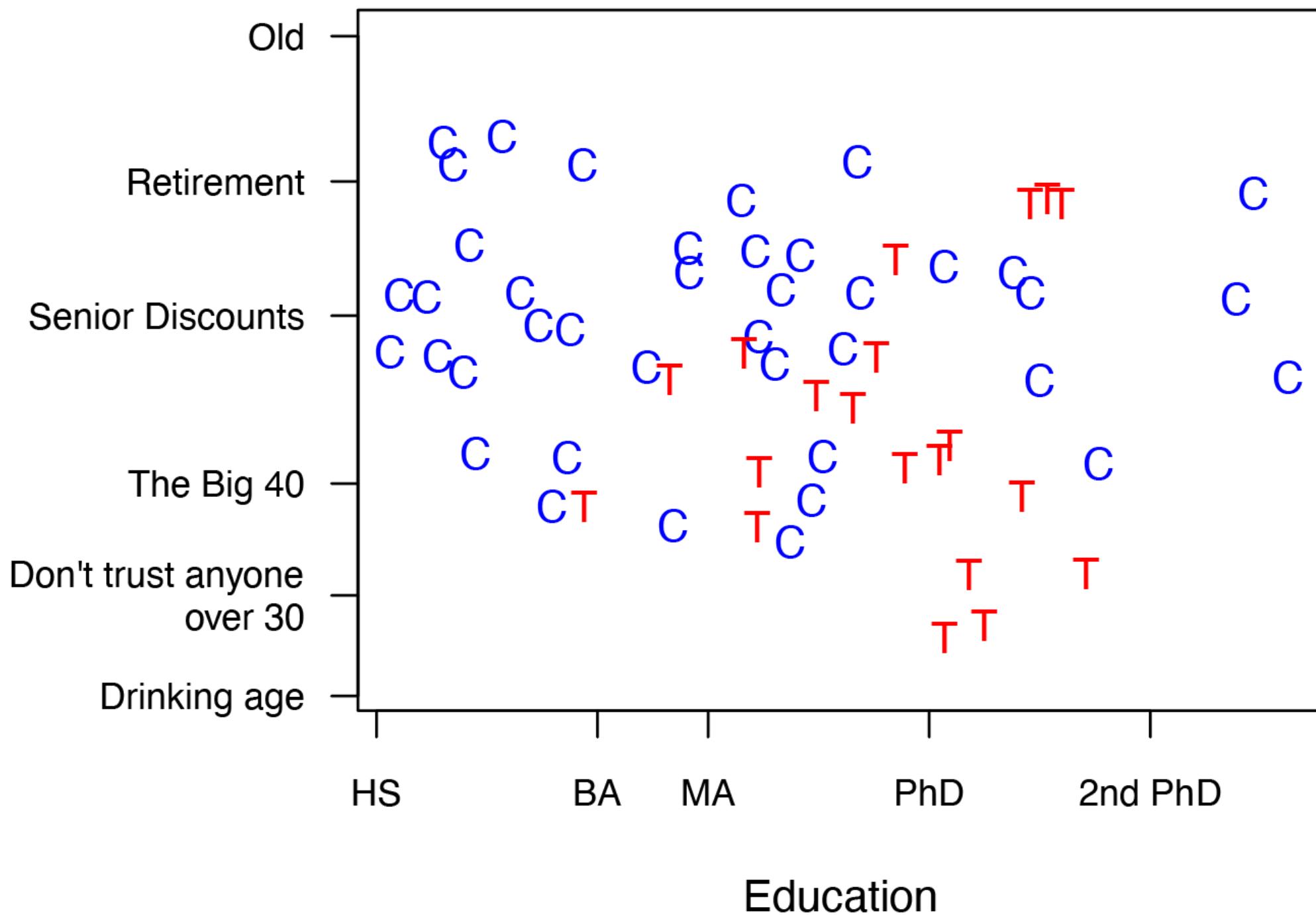
Use rules to partition data into clusters

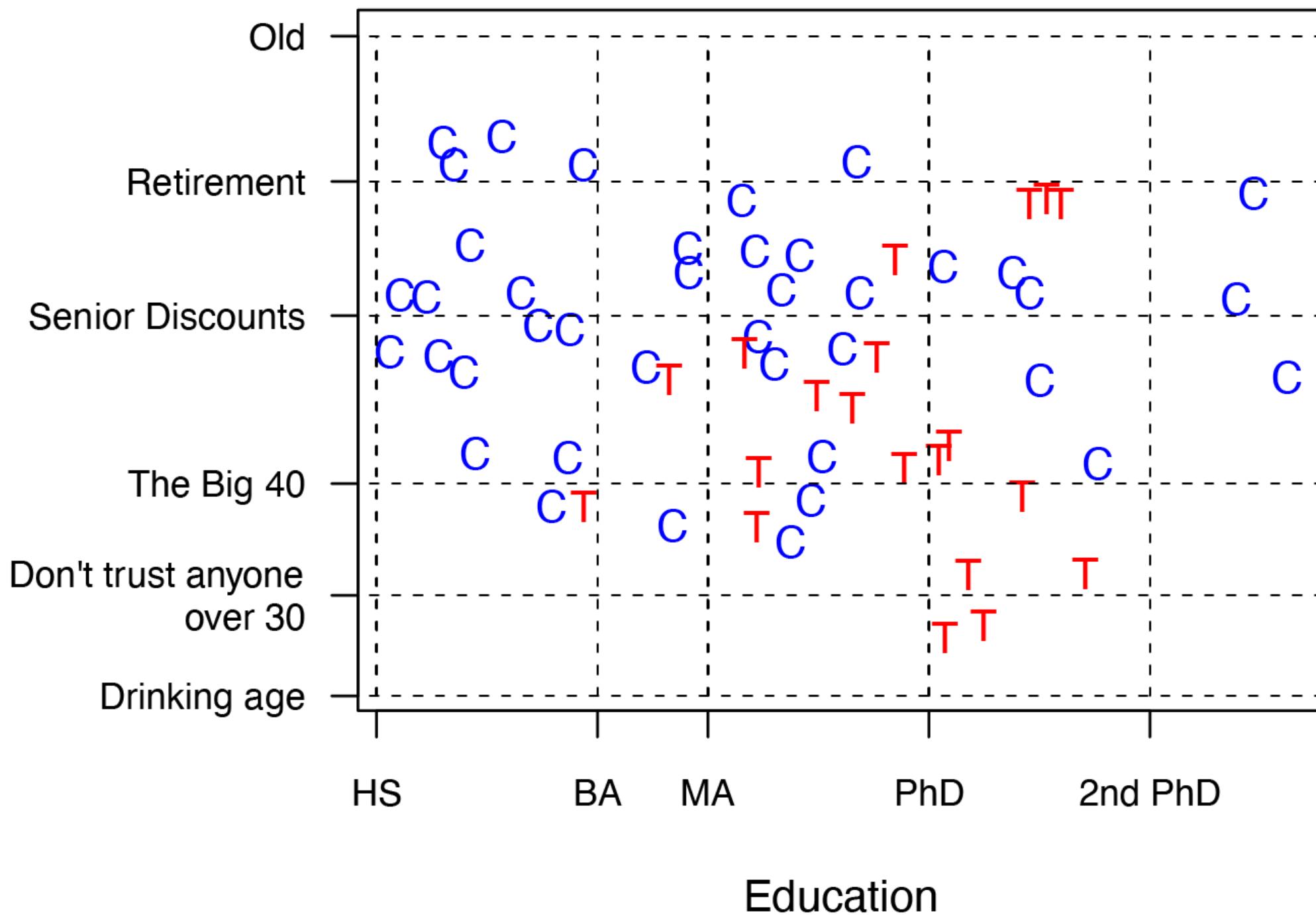
Treatment should be
random within clusters

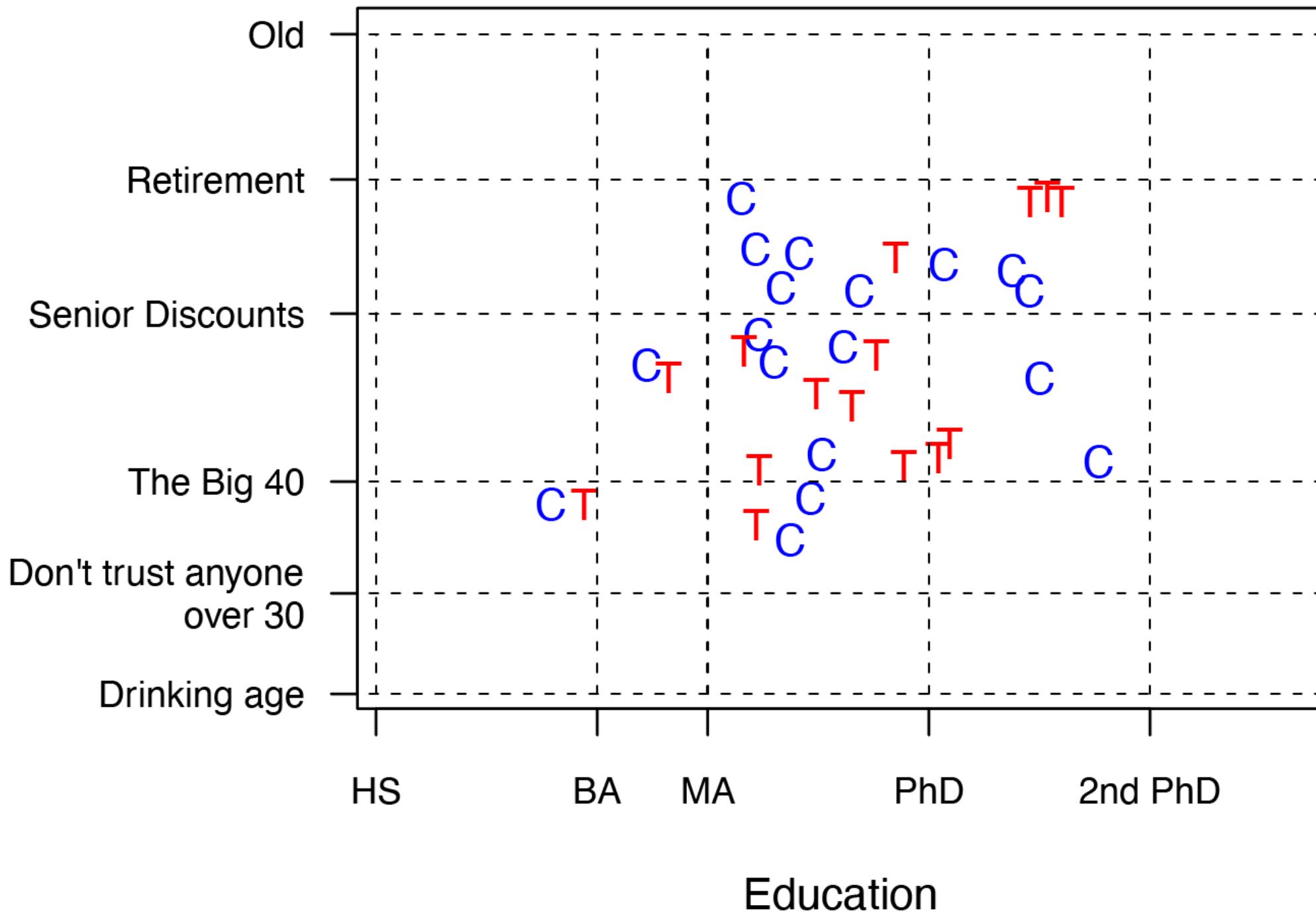
Unconfoundedness again!

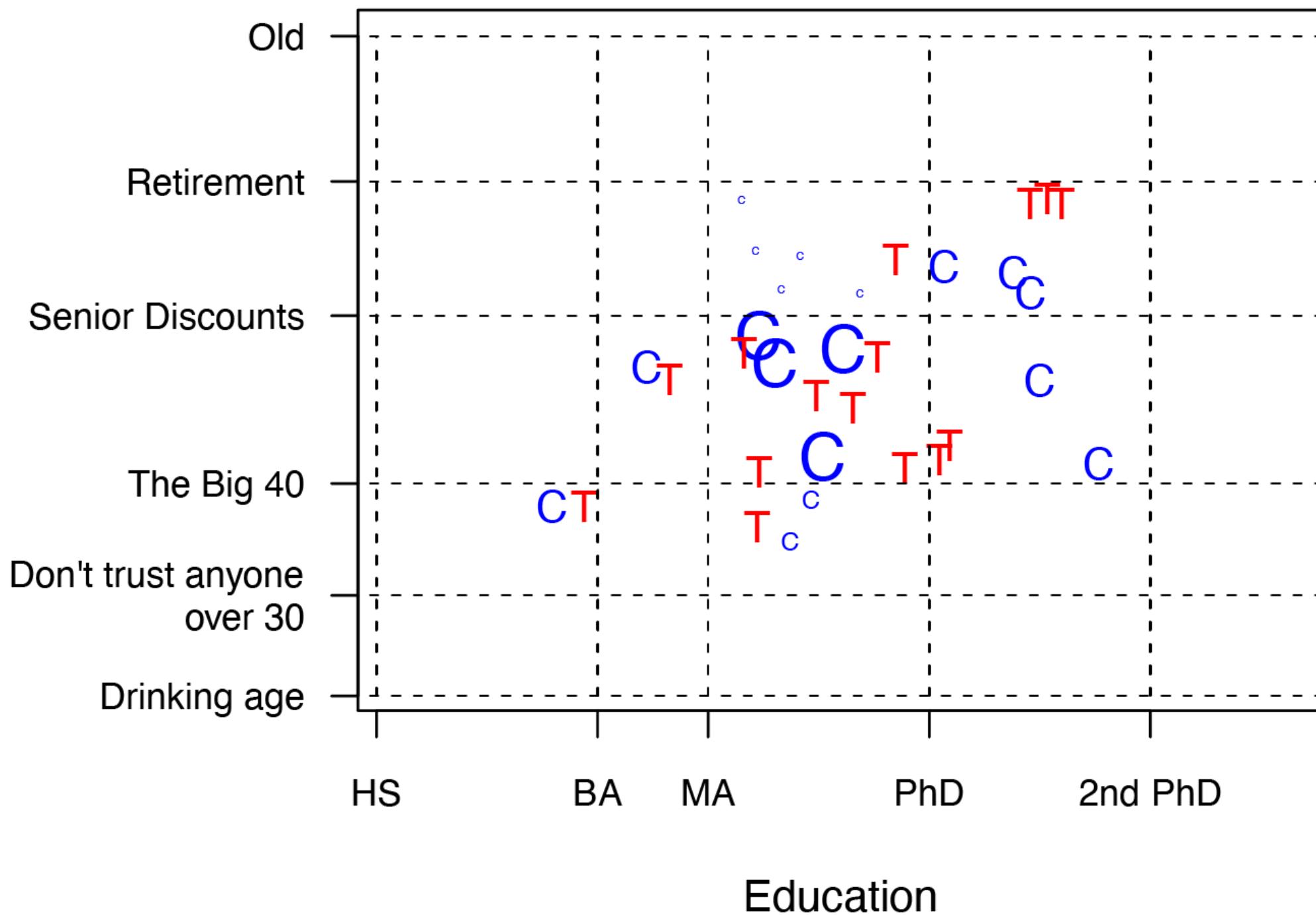
Some clusters will be more/less important

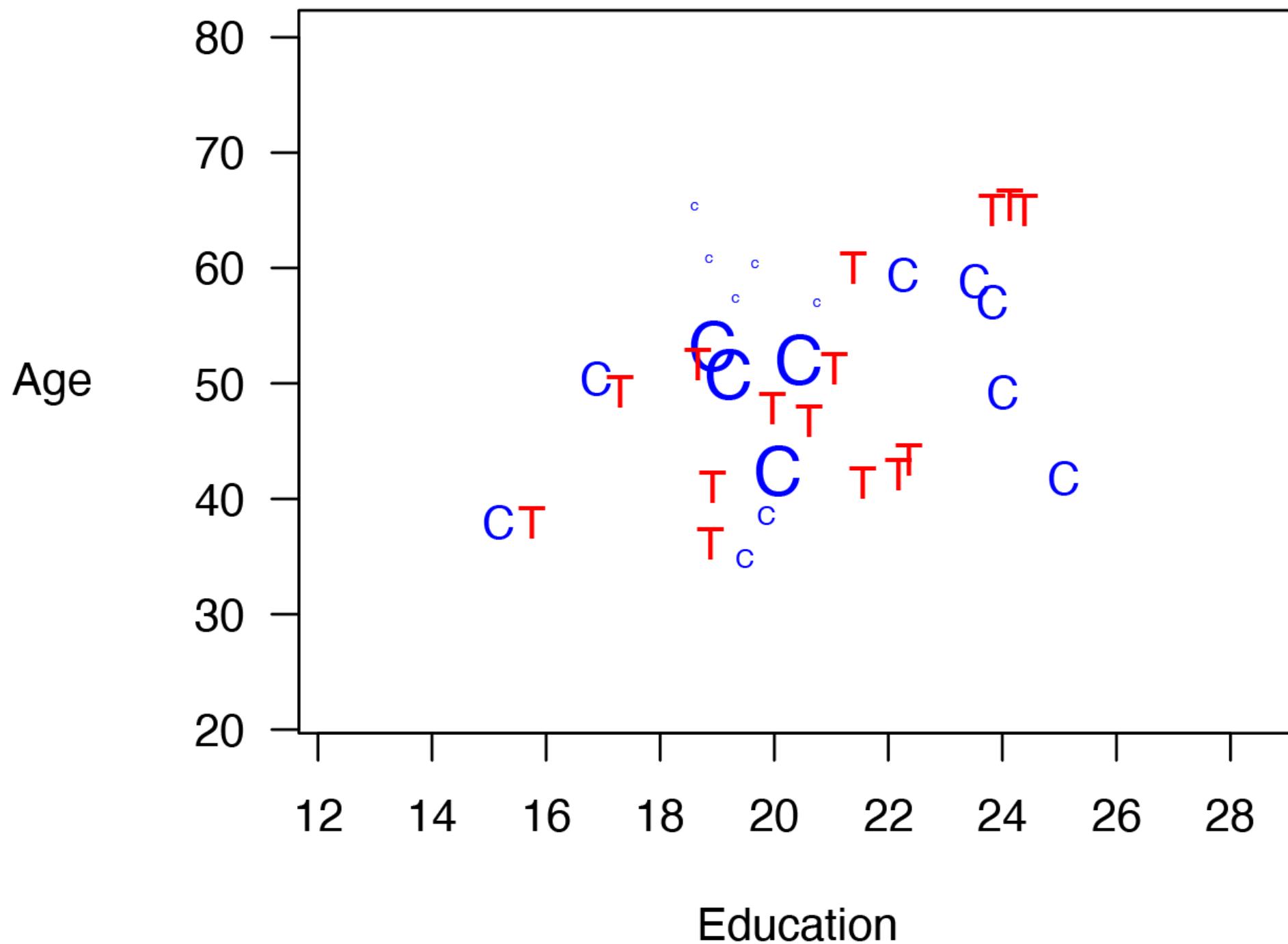






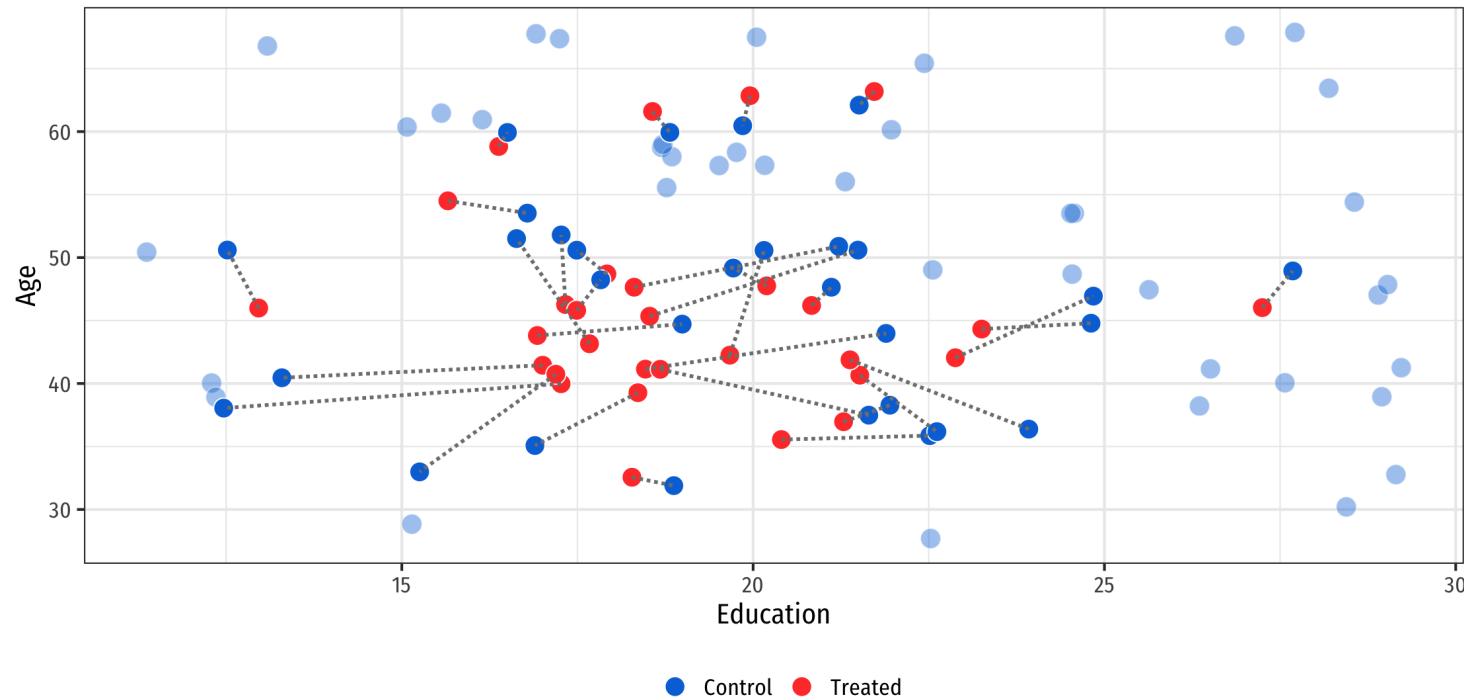






Potential problems with matching

Nearest neighbor matching and CEM can be greedy!



Solution: Don't throw everything away

Propensity scores

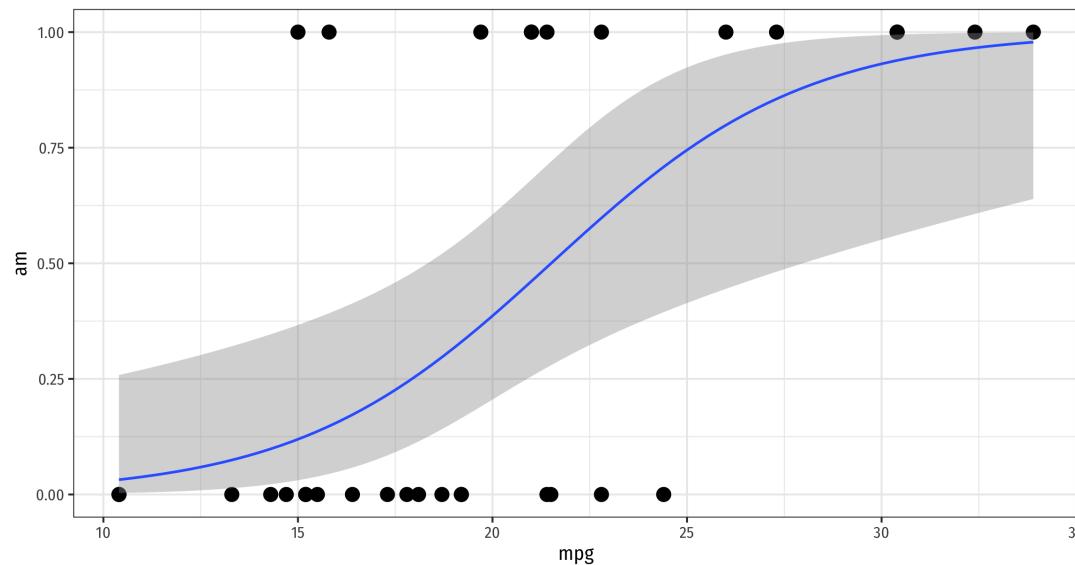
Predict the probability of assignment
to treatment using a model

Logistic regression, probit regression, machine learning

$$\log \frac{p_{\text{Treatment}}}{1 - p_{\text{Treatment}}} = \beta_0 + \beta_1 \text{Education} + \beta_2 \text{Age}$$

$$\log \frac{p_{\text{Manual}}}{1 - p_{\text{Manual}}} = \beta_0 + \beta_1 \text{MPG}$$

```
model_transmission <- glm(am ~ mpg, data = mtcars, family = binomial(link = "logit"))
```



```
> tidy(model_transmission)
# A tibble: 2 x 5
  term      estimate std.error statistic p.value
  <chr>      <dbl>     <dbl>      <dbl>    <dbl>
1 (Intercept) -6.60      2.35     -2.81  0.00498
2 mpg         0.307     0.115      2.67  0.00751
```

```
> tidy(model_transmission, exponentiate = TRUE)
# A tibble: 2 x 5
  term      estimate std.error statistic p.value
  <chr>      <dbl>     <dbl>      <dbl>    <dbl>
1 (Intercept) 0.00136    2.35     -2.81  0.00498
2 mpg         1.36       0.115      2.67  0.00751
```

Plug all the values of MPG into the model and find the predicted probability

```
augment(model_transmission, data = mtcars, type.predict ="response")
```

```
# A tibble: 32 x 3
  mpg     am propensity
  <dbl> <dbl>      <dbl>
1 21       1     0.461
2 21       1     0.461
3 22.8     1     0.598
4 21.4     0     0.492
5 18.7     0     0.297
6 18.1     0     0.260
7 14.3     0     0.0986
8 24.4     0     0.708
9 22.8     0     0.598
10 19.2    0     0.330
# ... with 22 more rows
```

Highly unlikely
to be manual

Highly likely to
be manual (1)

Propensity score matching

Super popular method

There are mathy reasons why
it's not great for matching

Propensity scores are fine!
Using them for matching isn't!

Why Propensity Scores Should Not Be Used for Matching

Gary King^{ID1} and Richard Nielsen^{ID2}

¹ Institute for Quantitative Social Science, Harvard University, 1737 Cambridge Street, Cambridge, MA 02138, USA.

Email: king@harvard.edu, URL: <http://GaryKing.org>

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USA. Email: rnielsen@mit.edu, URL: <http://www.mit.edu/~rnielsen>

Abstract

We show that propensity score matching (PSM), an enormously popular method of preprocessing data for causal inference, often accomplishes the opposite of its intended goal—thus increasing imbalance, inefficiency, model dependence, and bias. The weakness of PSM comes from its attempts to approximate a completely randomized experiment, rather than, as with other matching methods, a more efficient fully blocked randomized experiment. PSM is thus uniquely blind to the often large portion of imbalance that can be eliminated by approximating full blocking with other matching methods. Moreover, in data balanced enough to approximate complete randomization, either to begin with or after pruning some observations, PSM approximates random matching which, we show, increases imbalance even relative to the original data. Although these results suggest researchers replace PSM with one of the other available matching methods, propensity scores have other productive uses.

Keywords: matching, propensity score matching, coarsened exact matching, Mahalanobis distance matching, model dependence

<https://www.youtube.com/watch?v=rBv39pK1iEs>

Weighting in general

Make some observations more important than others

	Young	Middle	Old
Population	30%	40%	30%
Sample	60%	30%	10%

Weighting in general

Make some observations more important than others

	Young	Middle	Old
Population	30%	40%	30%
Sample	60%	30%	10%
Weight	$30 / 60 = 0.5$	$40 / 30 = 1.333$	$30 / 10 = 3$

Multiply weights by average values (or use in regression) to adjust for importance

Inverse probability weighting

Use propensity scores to weight observations by how “weird” they are

Observations with high probability of treatment who don’t get it (and vice versa) have higher weight

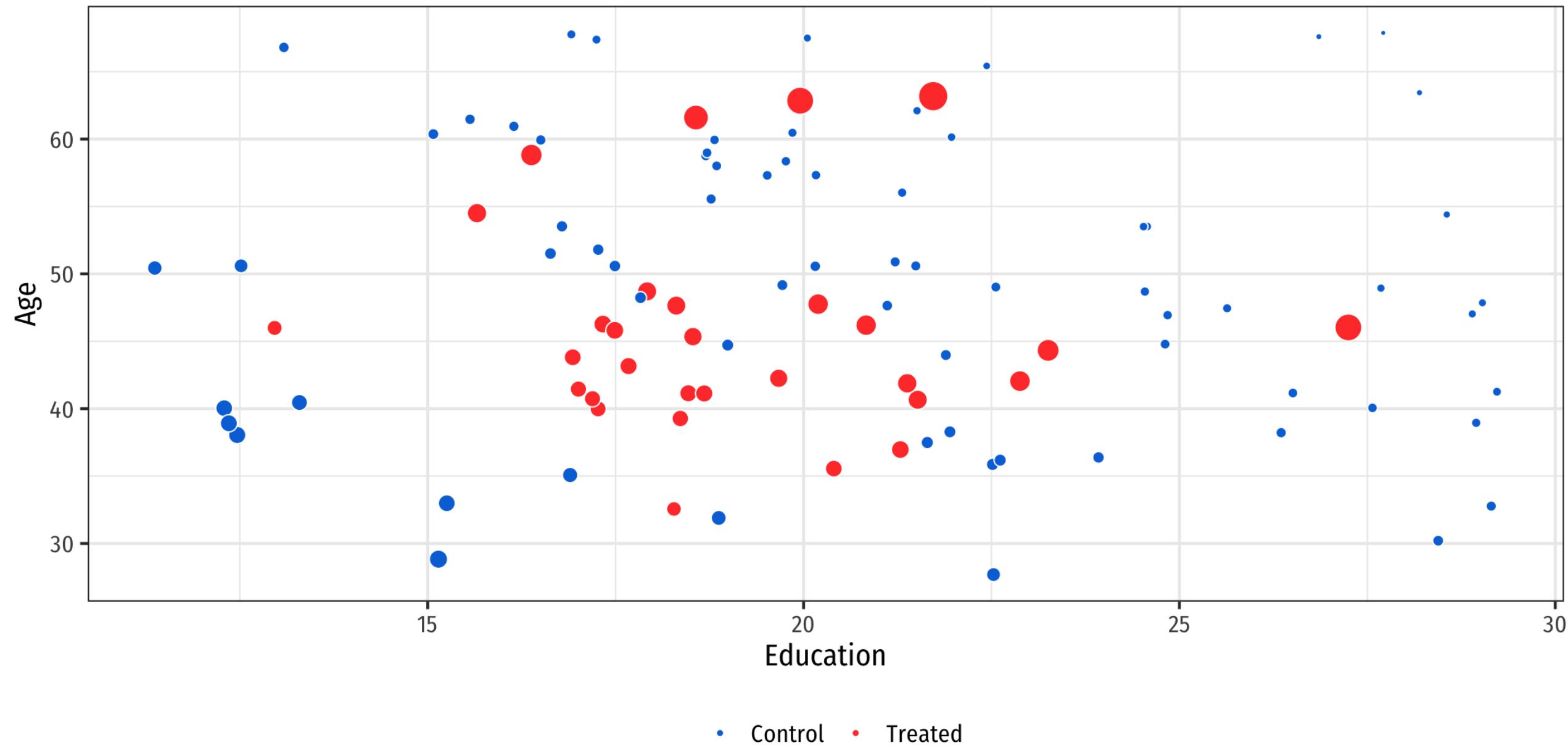
$$\frac{\text{Treatment}}{\text{Propensity}} + \frac{1 - \text{Treatment}}{1 - \text{Propensity}}$$

```
augment(model_transmission, data = mtcars,  
       type.predict = "response") %>%  
  select(mpg, am, propensity = .fitted) %>%  
  mutate(ip_weight = (am / propensity) +  
            ((1 - am) / (1 - propensity)))
```

```
# A tibble: 32 x 4  
  mpg     am propensity ip_weight  
  <dbl> <dbl>      <dbl>      <dbl>  
1 21      1        0.461      2.17  
2 21      1        0.461      2.17  
3 22.8    1        0.598      1.67  
4 21.4    0        0.492      1.97  
5 18.7    0        0.297      1.42  
6 18.1    0        0.260      1.35  
7 14.3    0        0.0986     1.11  
8 24.4    0        0.708      3.43  
9 22.8    0        0.598      2.49  
10 19.2   0        0.330      1.49  
# ... with 22 more rows
```

Unlikely to be
manual and isn't

Highly likely to be
manual but isn't.
Weird!



Other weights

This gets you the ATE

Other versions
of weights

(Z = treatment;
 e = propensity score)

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

$$w_{ATE} = \frac{Z_i}{e_i} + \frac{1-Z_i}{1-e_i}$$

$$w_{ATT} = \frac{e_i Z_i}{e_i} + \frac{e_i(1-Z_i)}{1-e_i}$$

$$w_{ATC} = \frac{(1-e_i)Z_i}{e_i} + \frac{(1-e_i)(1-Z_i)}{1-e_i}$$

$$w_{ATM} = \frac{\min\{e_i, 1-e_i\}}{Z_i e_i + (1-Z_i)(1-e_i)}$$

$$w_{AT0} = (1 - e_i)Z_i + e_i(1 - Z_i)$$

R example