Randomization & matching

Fill out your reading report on iCollege!

February 26, 2020

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

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

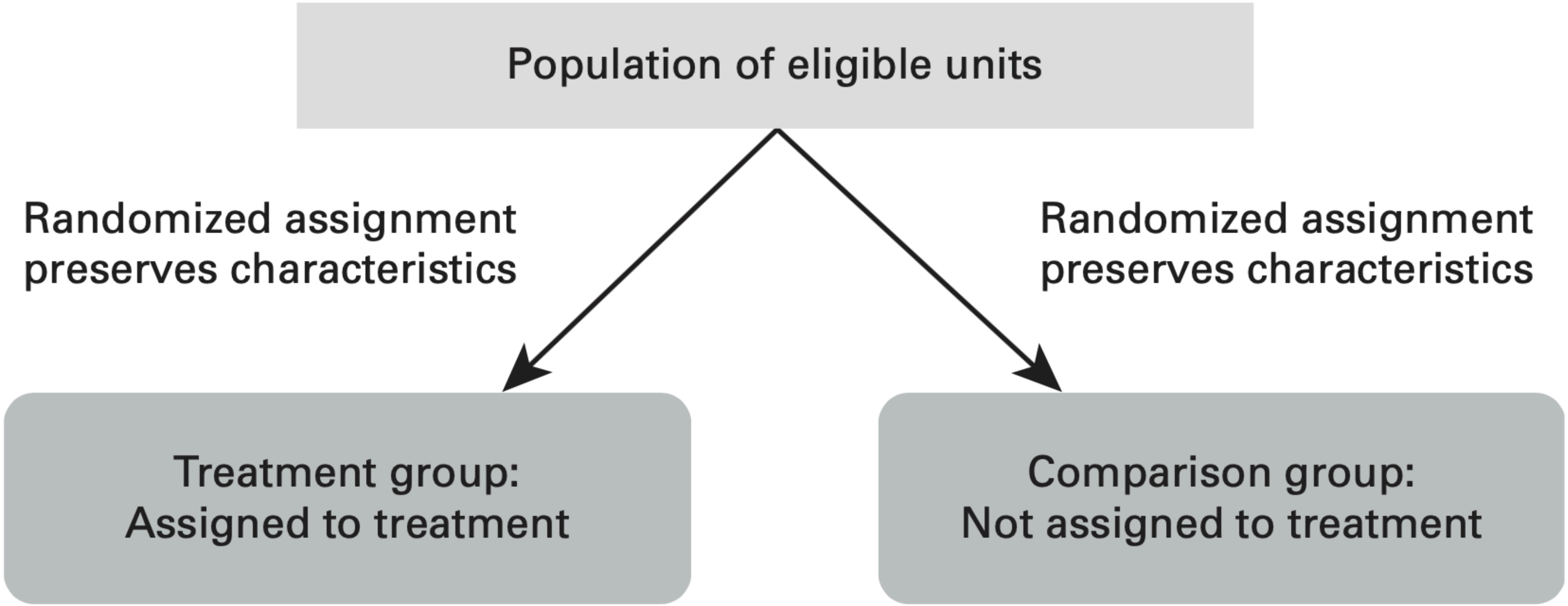
Why randomize?

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

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

Why randomize?

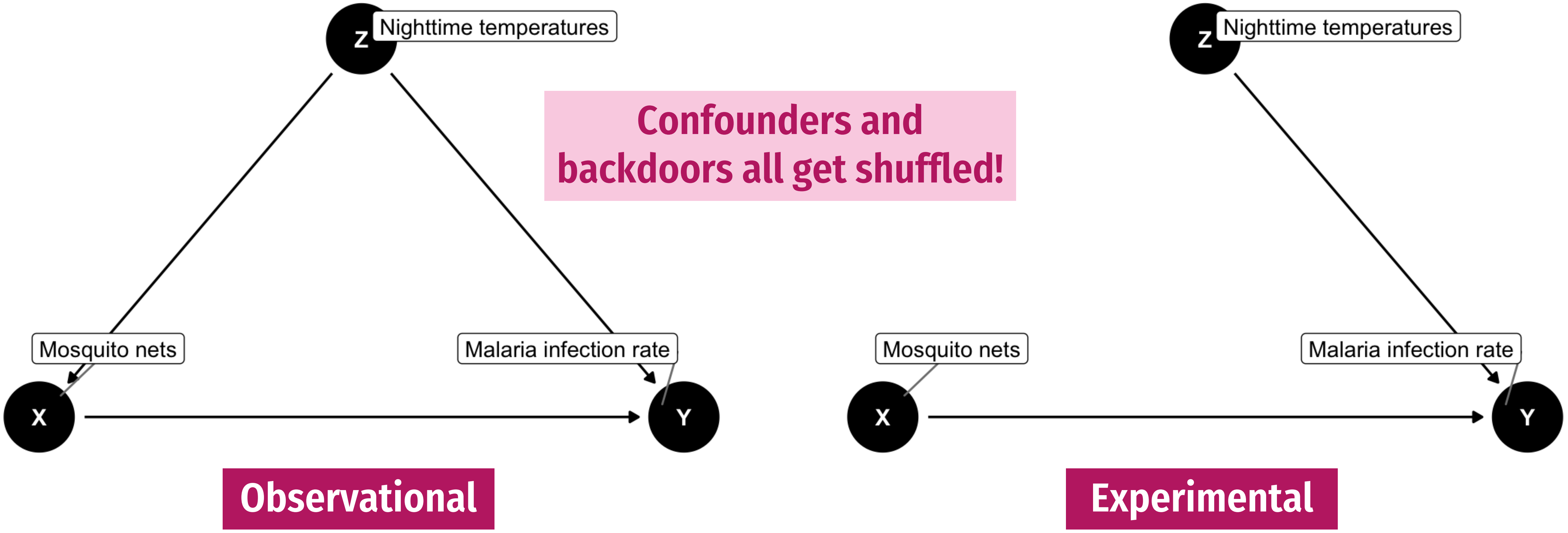
With big enough numbers, the magic of randomization helps make comparison groups comparable



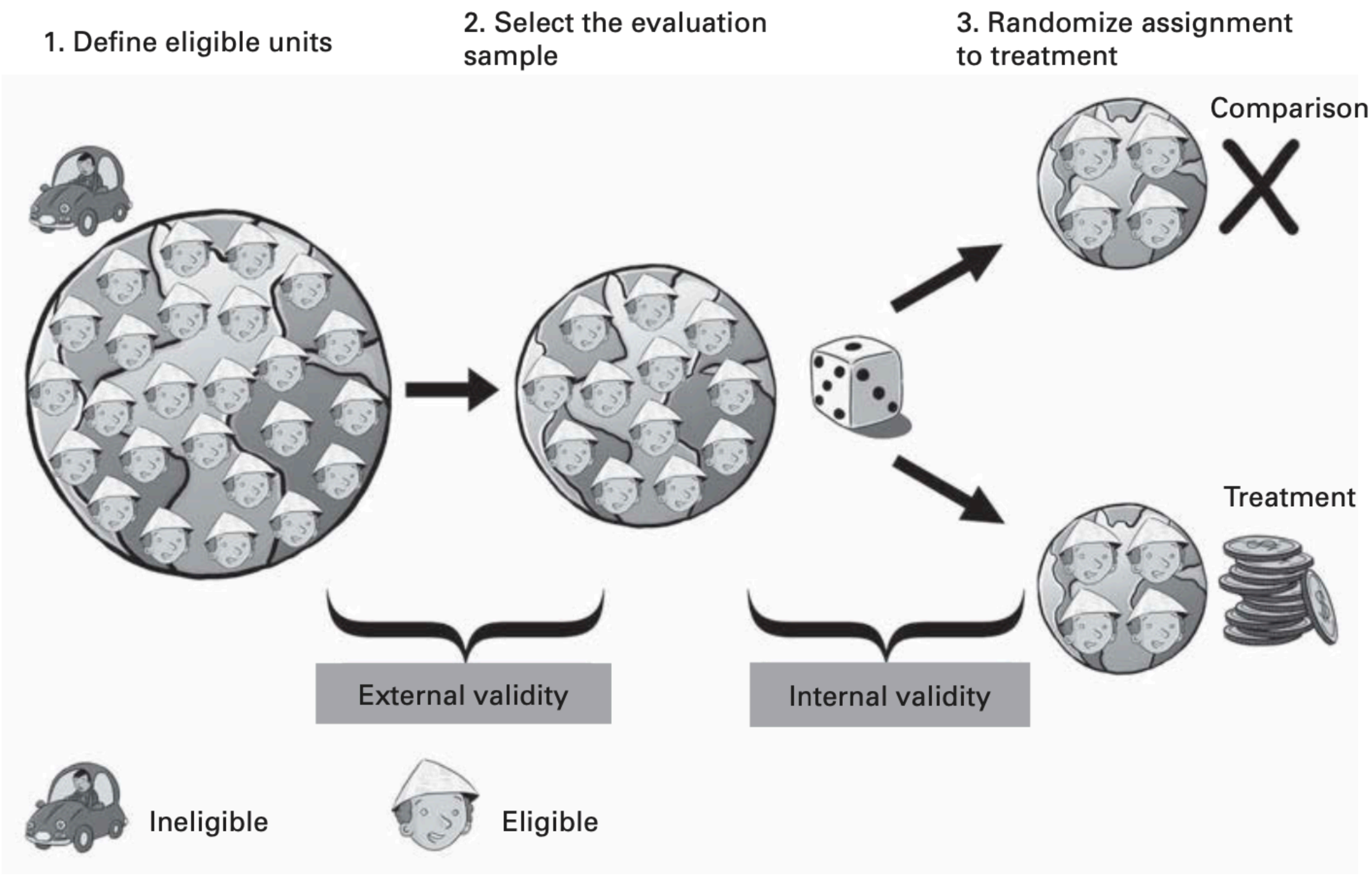
RCTs and DAGs

P(Malaria infection rate | *do*(Mosquito net))

When you *do*() X, remove all arrows into it



How to randomize?



Random assignment

Coins

Dice

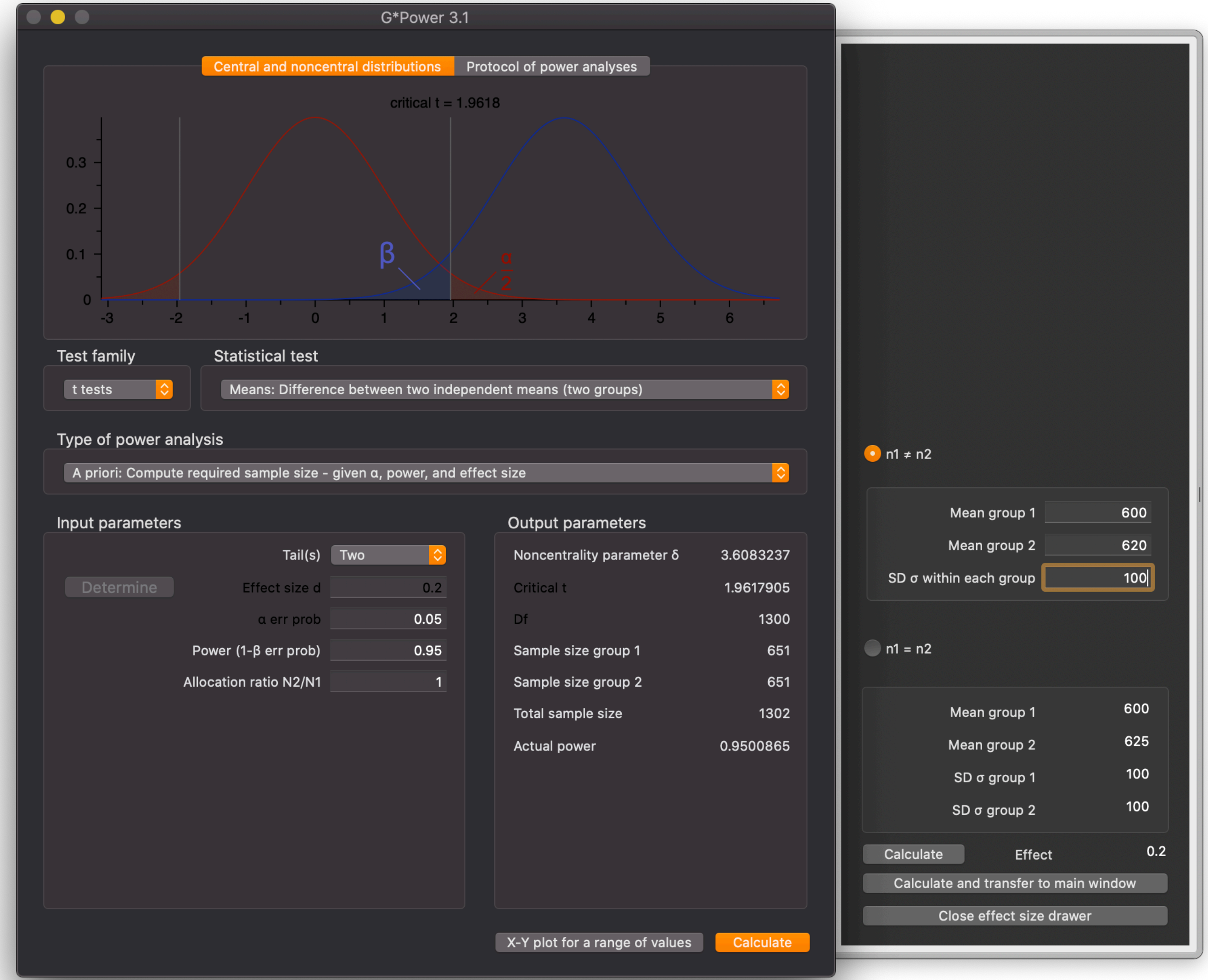
Unbiased lottery

Random numbers + threshold

Atmospheric noise

random.org

How big of a sample?



R example

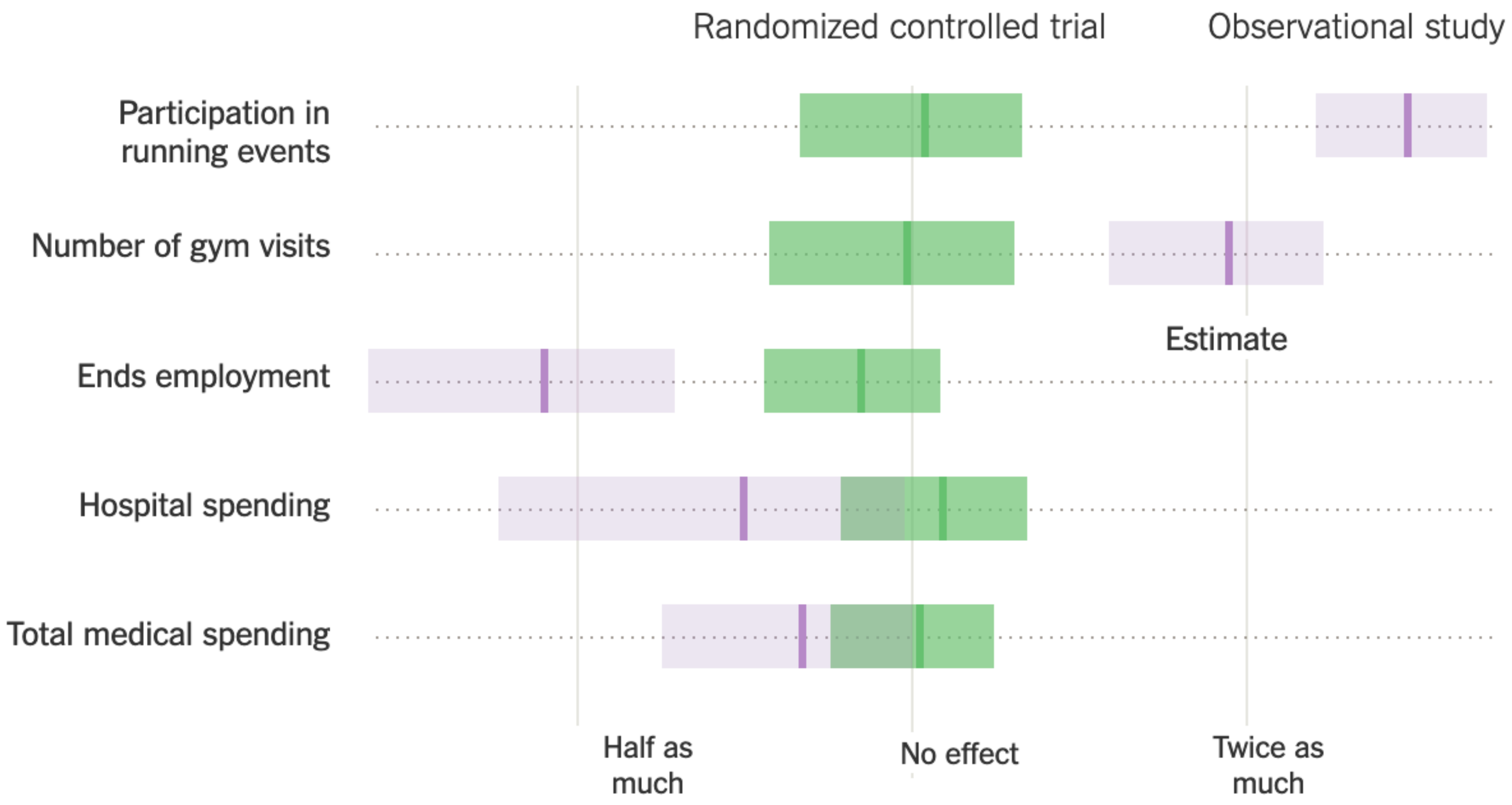
The “Gold” Standard

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

Google

rct "gold standard"

All Shopping News V

About 636,000 results (0.67 seconds)

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NIHMSID: NIHMS966617
PMID: 29916205

Author Manuscript

Randomised controlled trials—the gold standard for effectiveness research

Eduardo Hariton, MD, MBA[1] and Joseph J. Locascio, PhD[2]

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See other articles in PMC that cite the published article.

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!

The Washington Post

Democracy Dies in Darkness

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 hor
fellow MIT economist Abhijit Banerjee and Harvard's Michael Kremer

J-PAL

ABDUL LATIF JAMEEL POVERTY ACTION LAB

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

12 112 510

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 | SPONSORED FU 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
>
> Save
>
> 1 Comments
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> BCCL
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> 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

Vox

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	Student	Private: Ivy	Private: Leafy	Private: Smart	Public: All State	Public: Tall State	Public: Altered State	1996 earnings
A	1		Reject	Admit		Admit		110,000
	2		Reject	Admit		Admit		100,000
	3		Reject	Admit		Admit		110,000
B	4	Admit			Admit		Admit	60,000
	5	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.

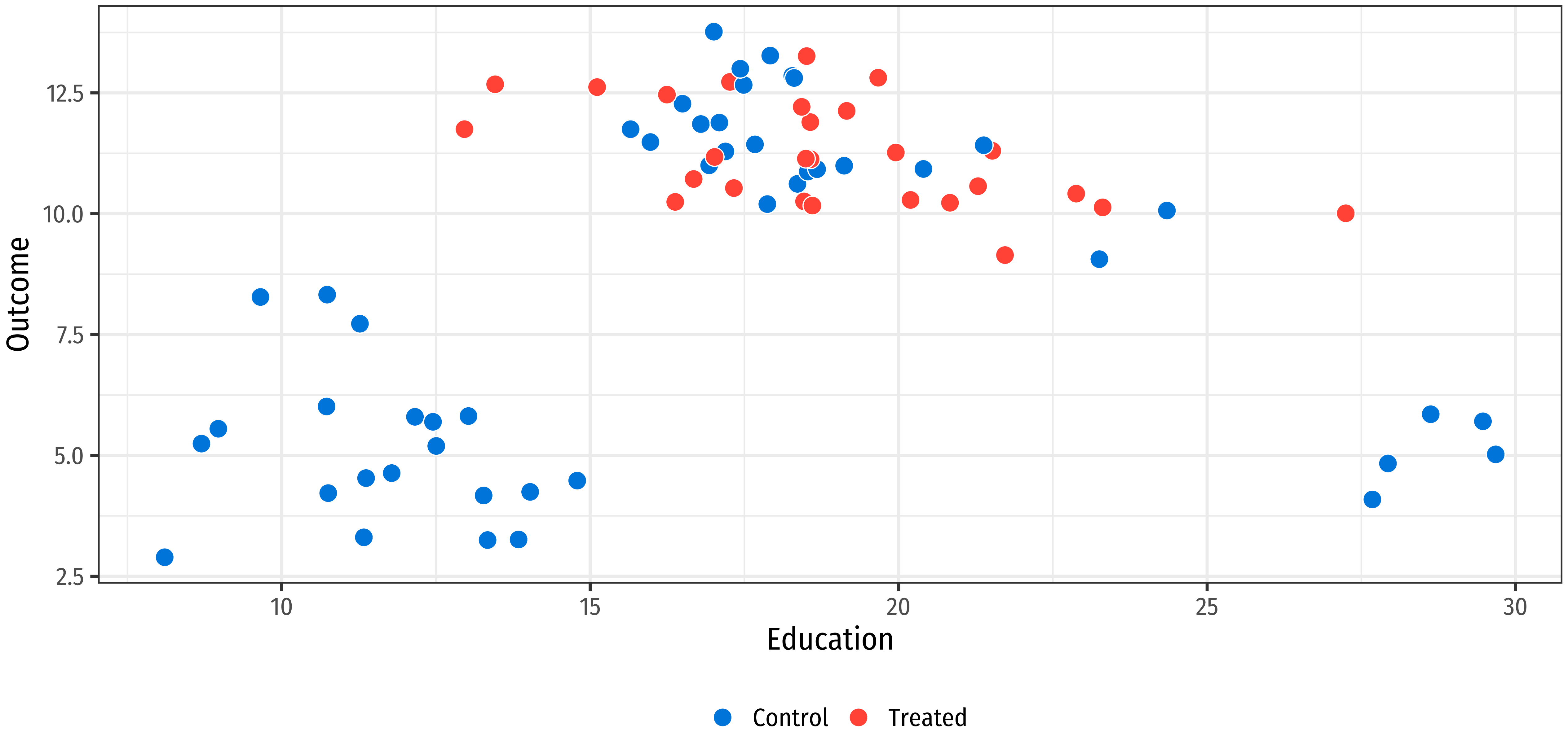
Why match?

Reduce model dependence

Imbalance → model dependence → researcher discretion → bias

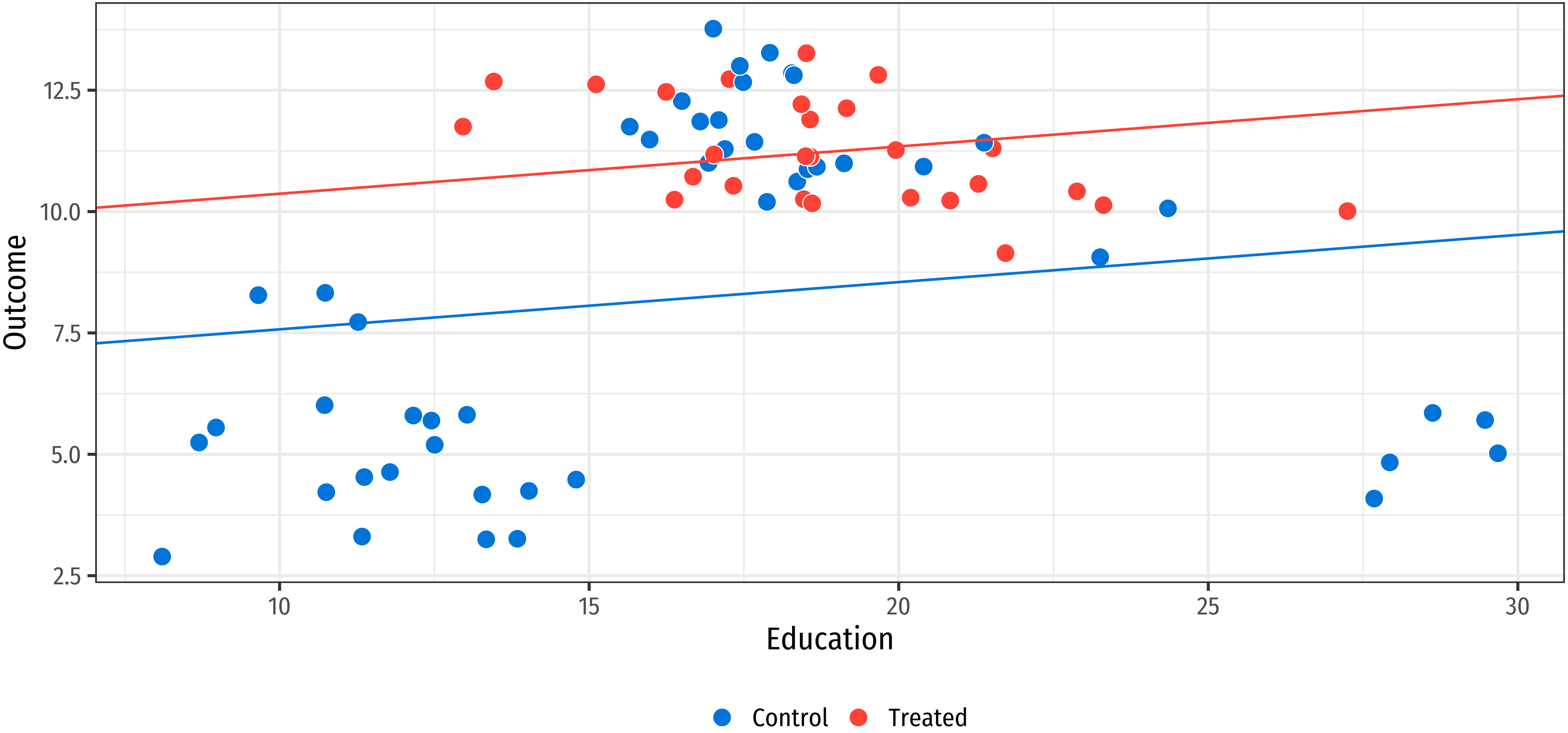
Compare apples to apples

It’s a way to adjust for backdoors!

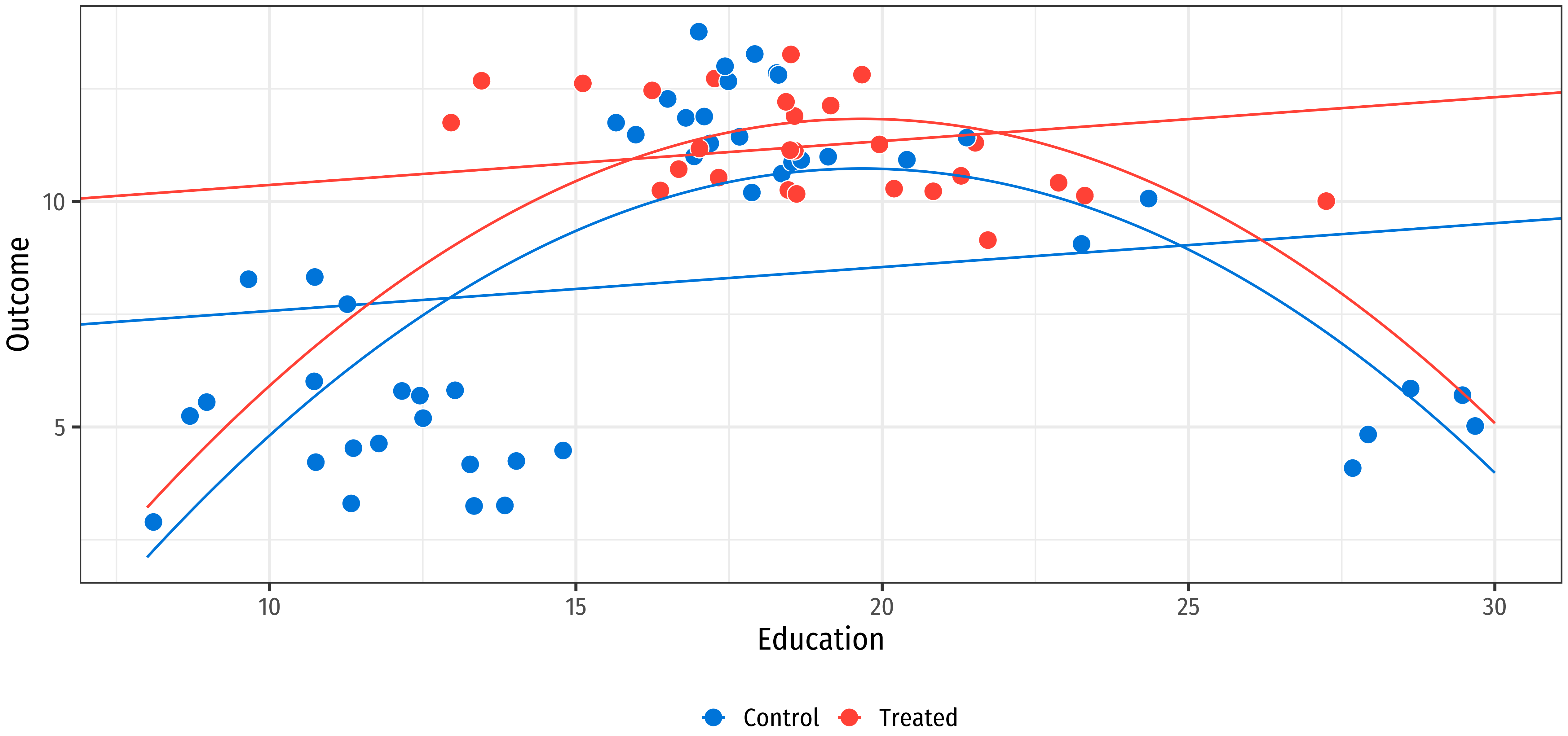


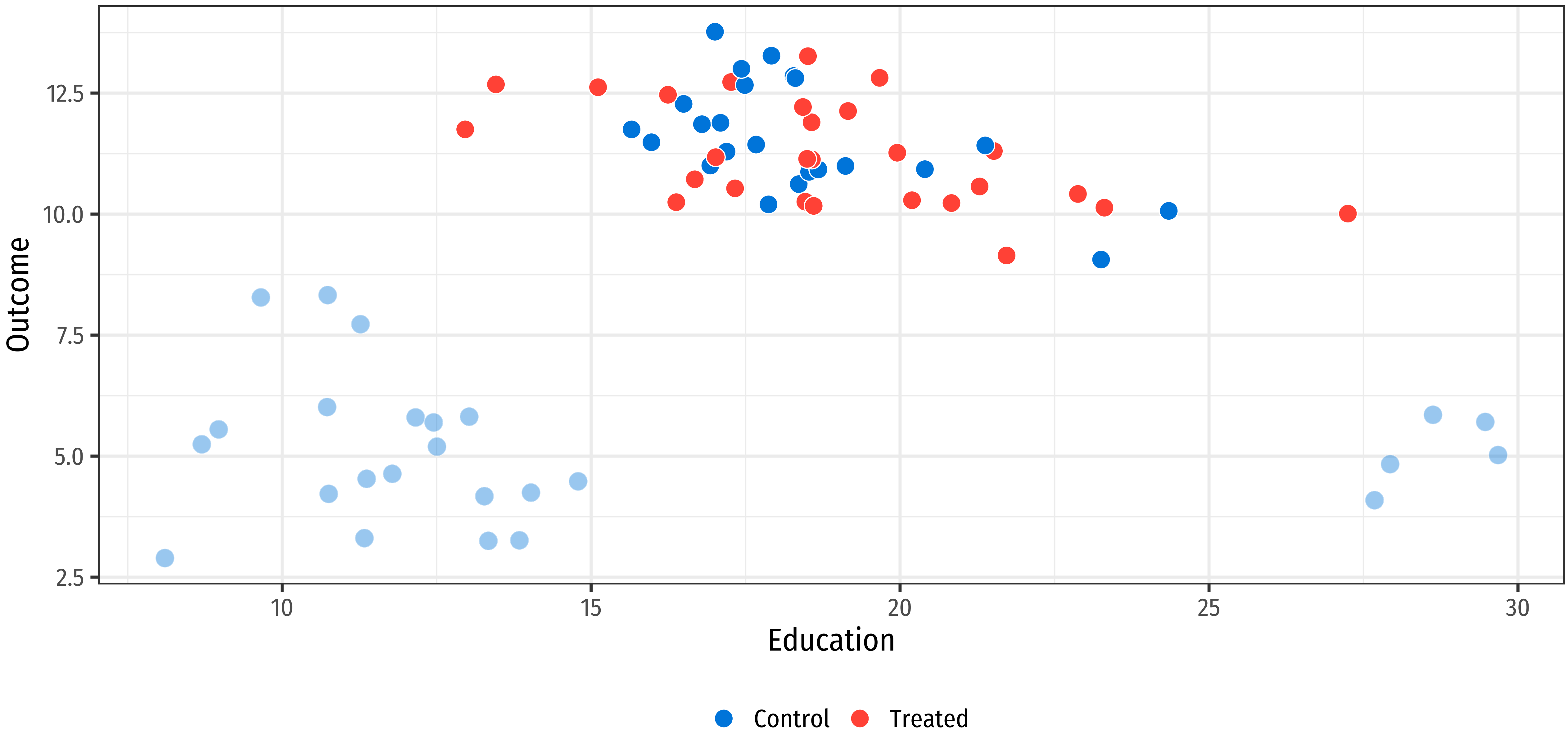
Outcome
12.5
10.0
7.5
5.0
2.5
10
15
20
25
30
Education
Control
Treated

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



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





Outcome
12.5
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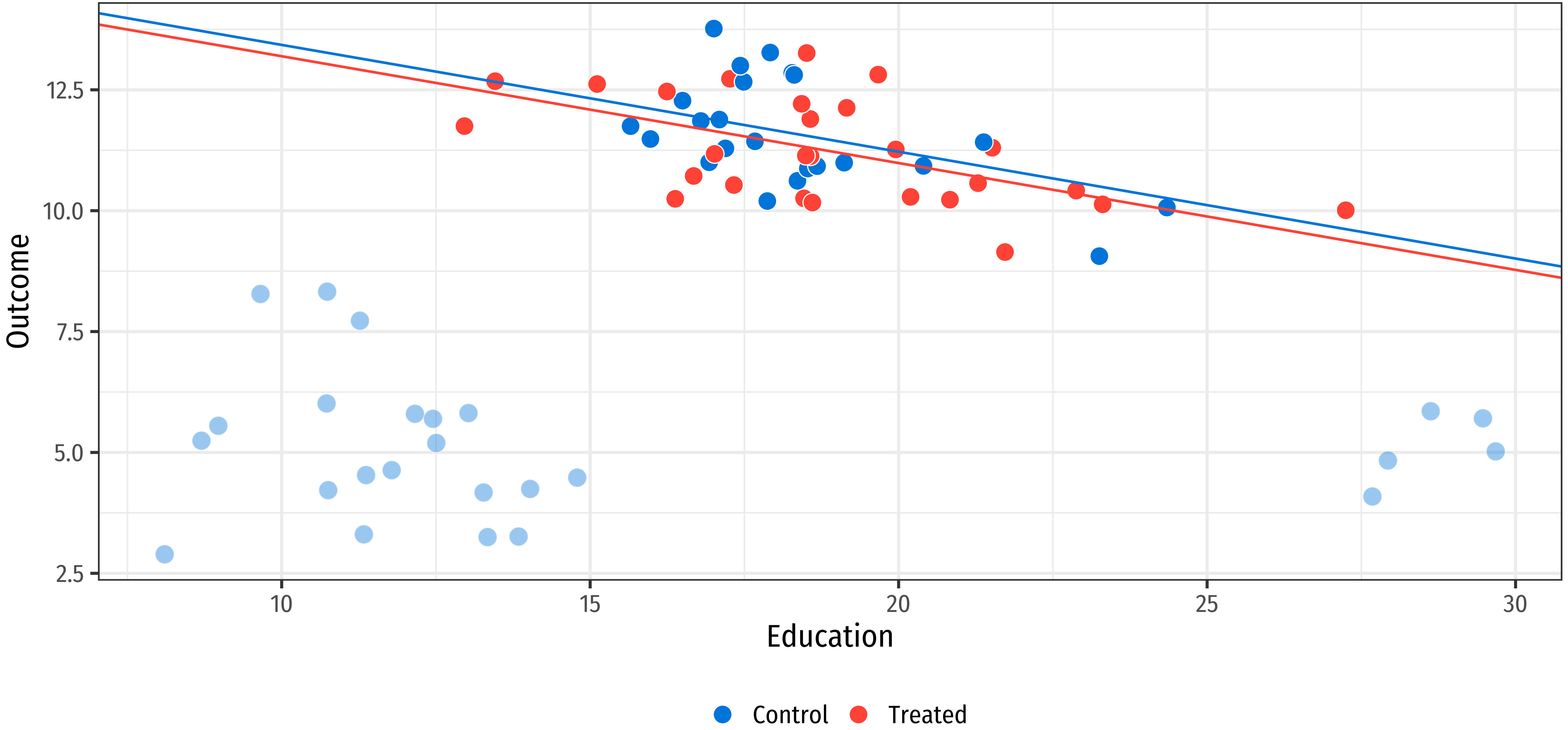
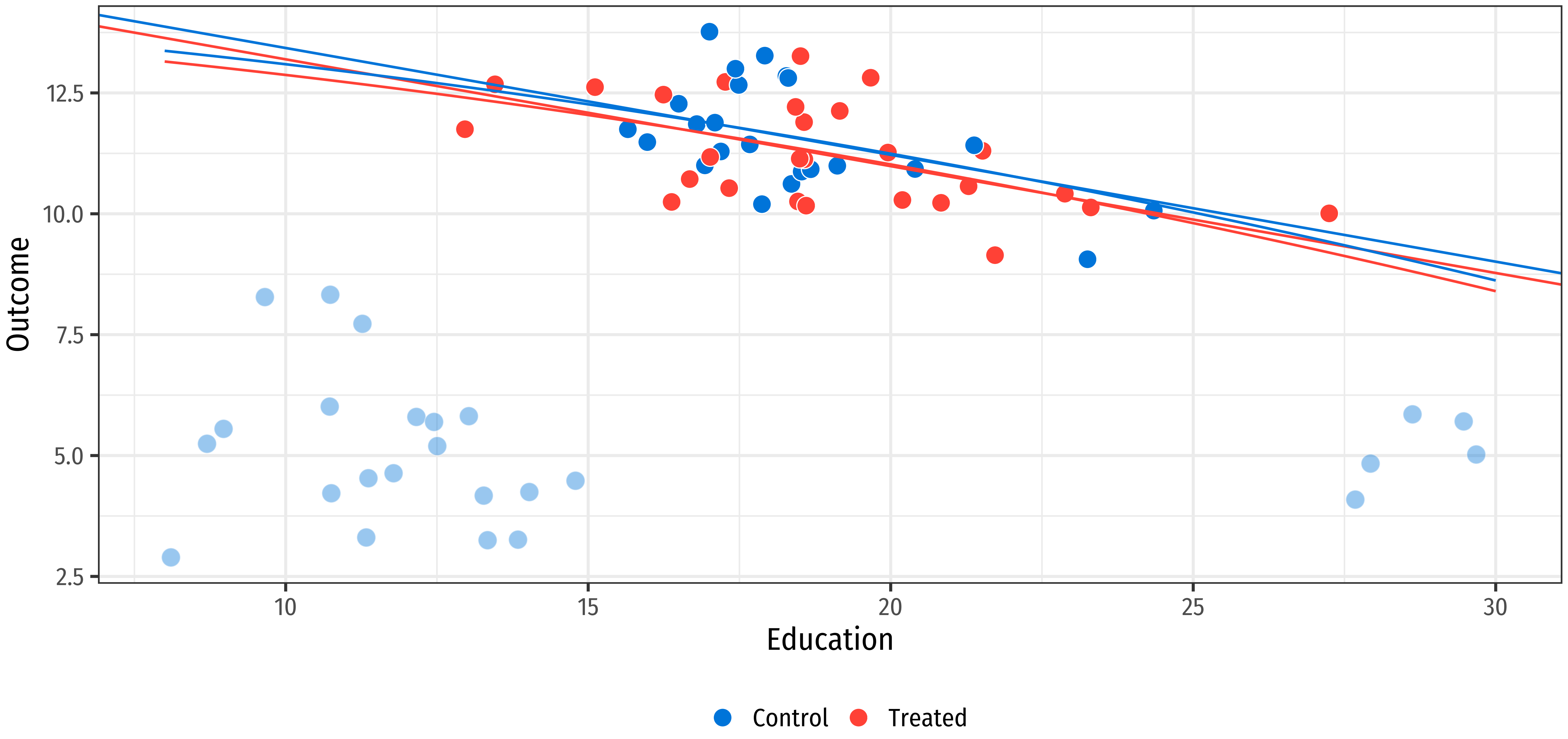
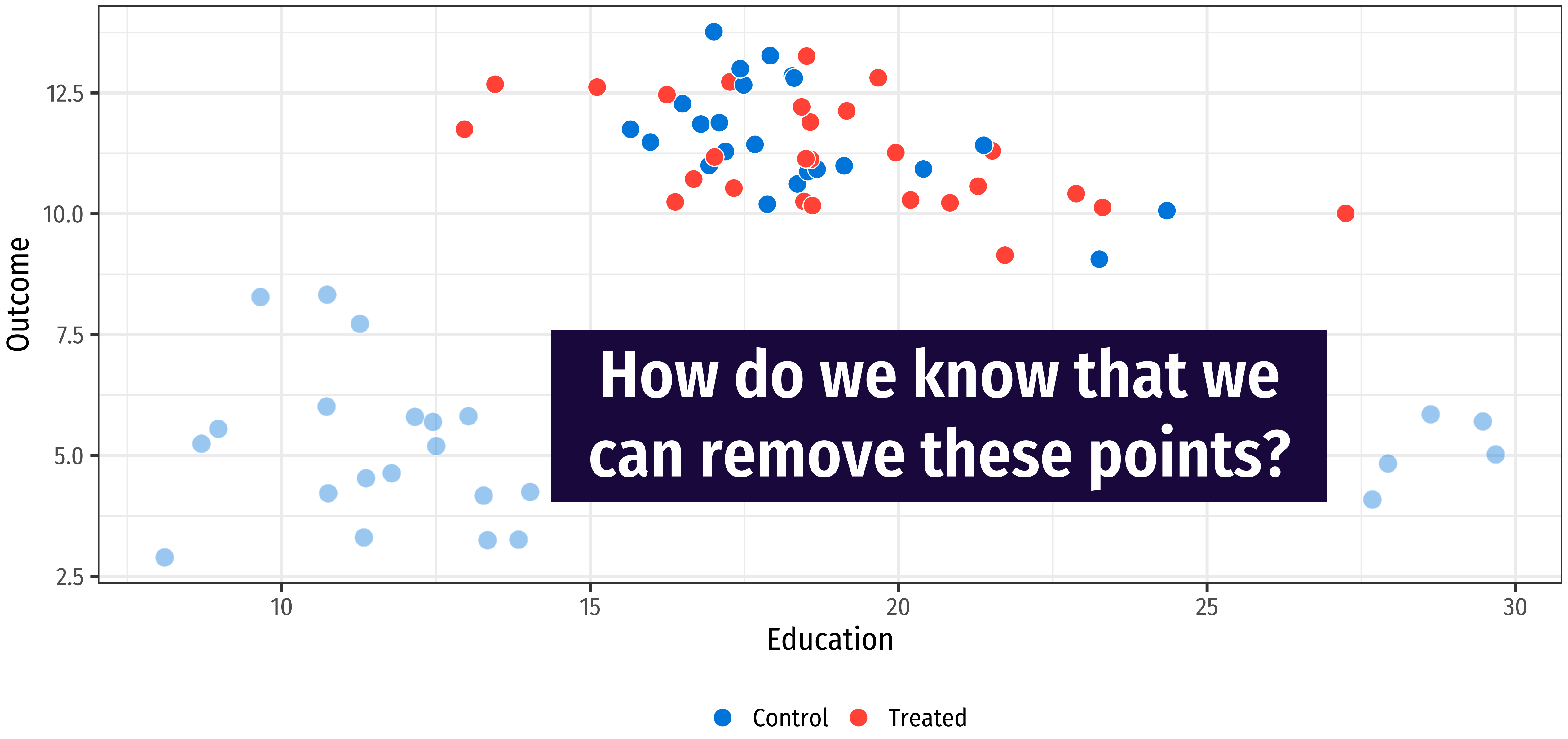
Education
Control
Treated

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



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




How do we know that we can remove these points?
Outcome
12.5
10.0
7.5
5.0
2.5
10
15
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Education
Control
Treated

General process for matching

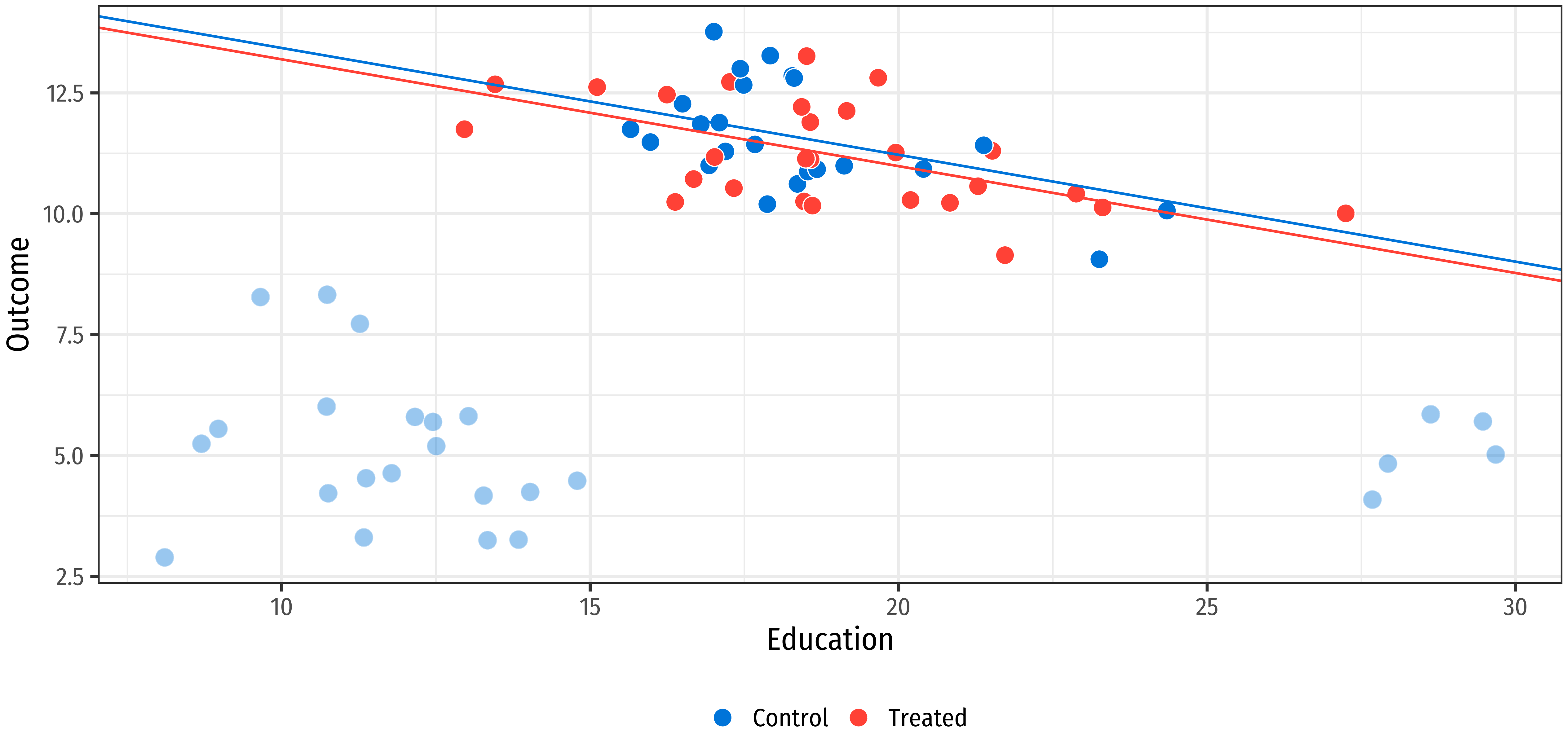
1. Preprocess data

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.



Outcome
12.5
10.0
7.5
5.0
2.5
10
15
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25
30
Education
Control
Treated

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

US MARKETS

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 researches 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

Coro
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Trum
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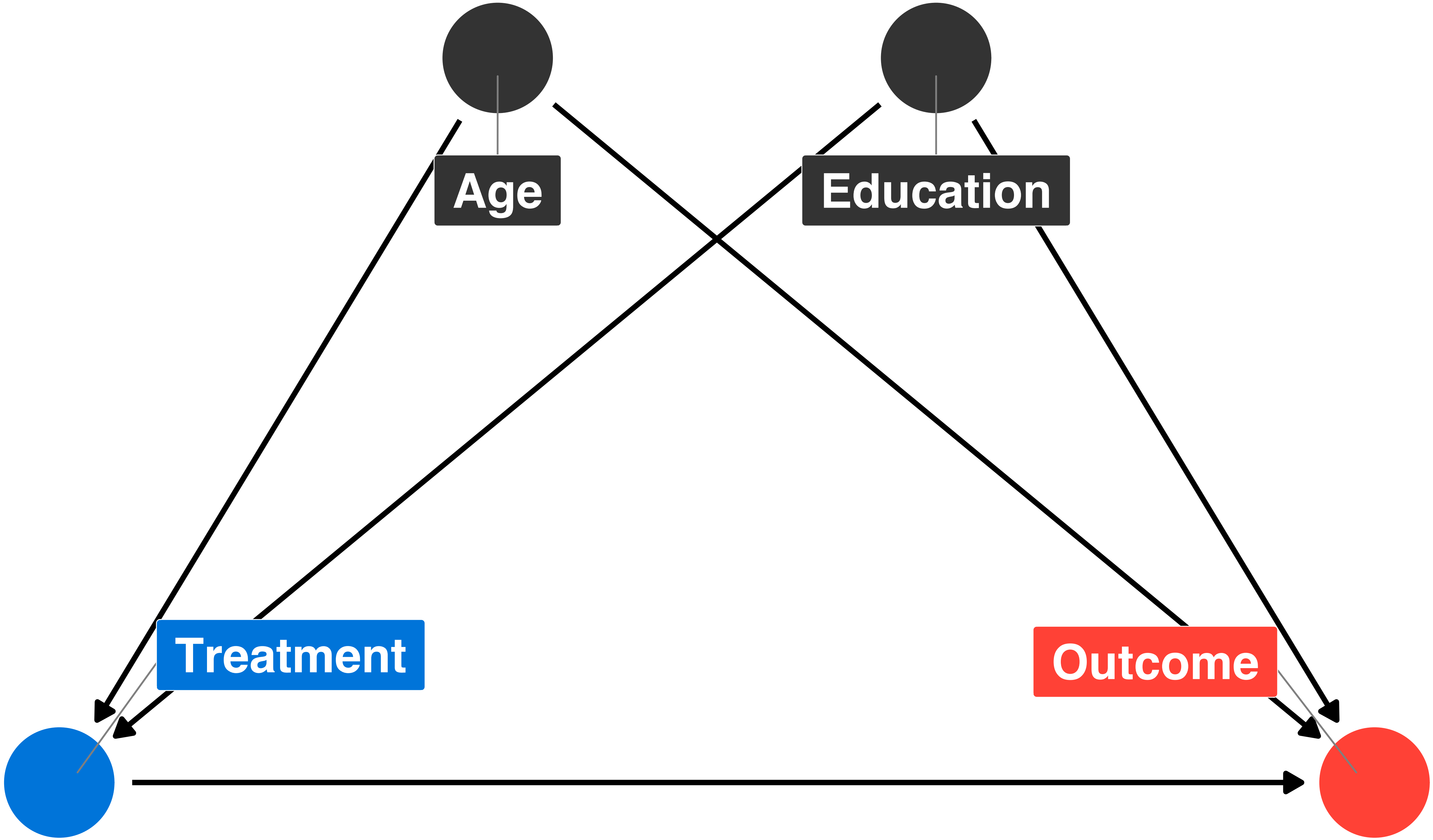
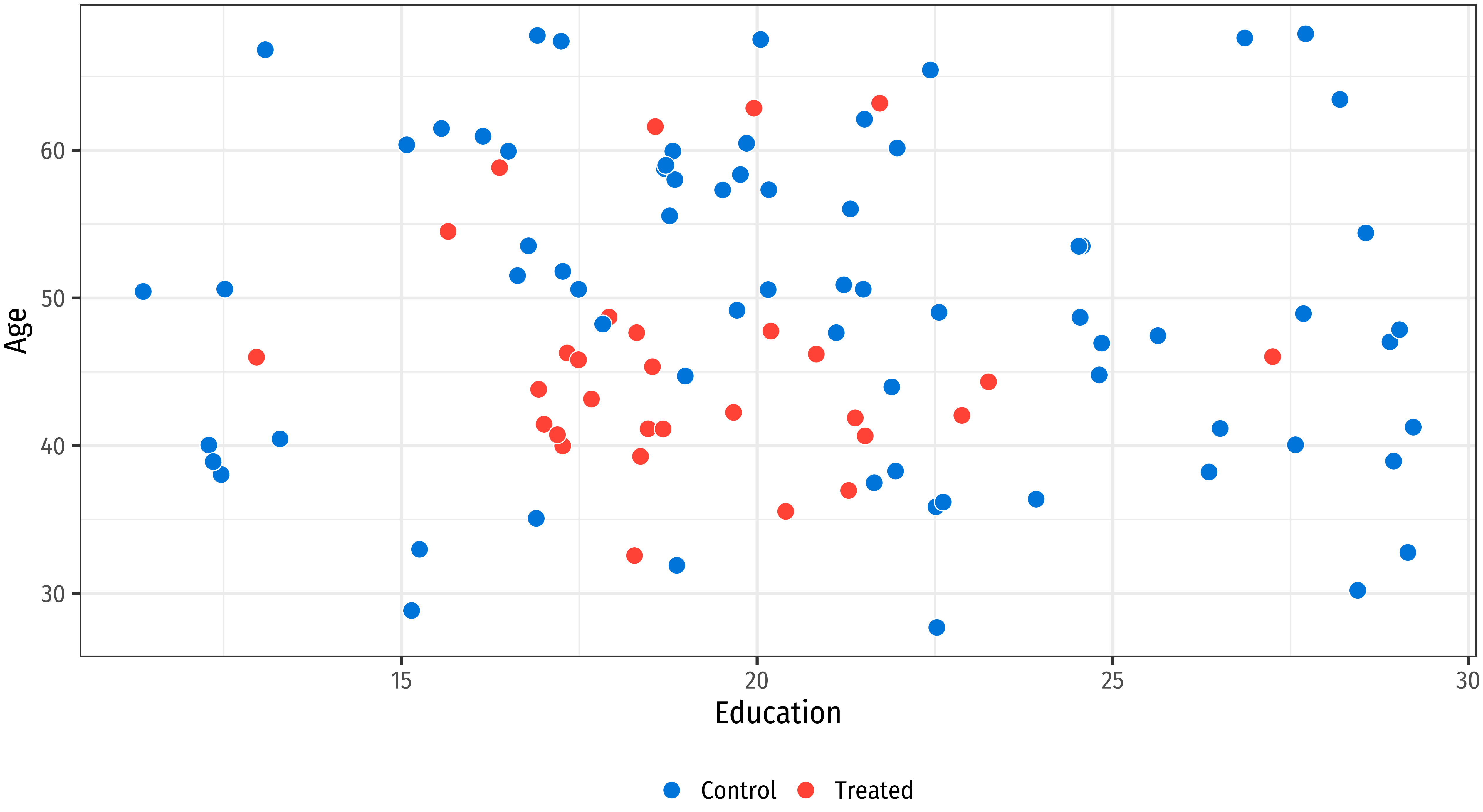
coror

Prasanta Chandra Mahalanobis

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


Age
Education
Treatment
Outcome



Age
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Education
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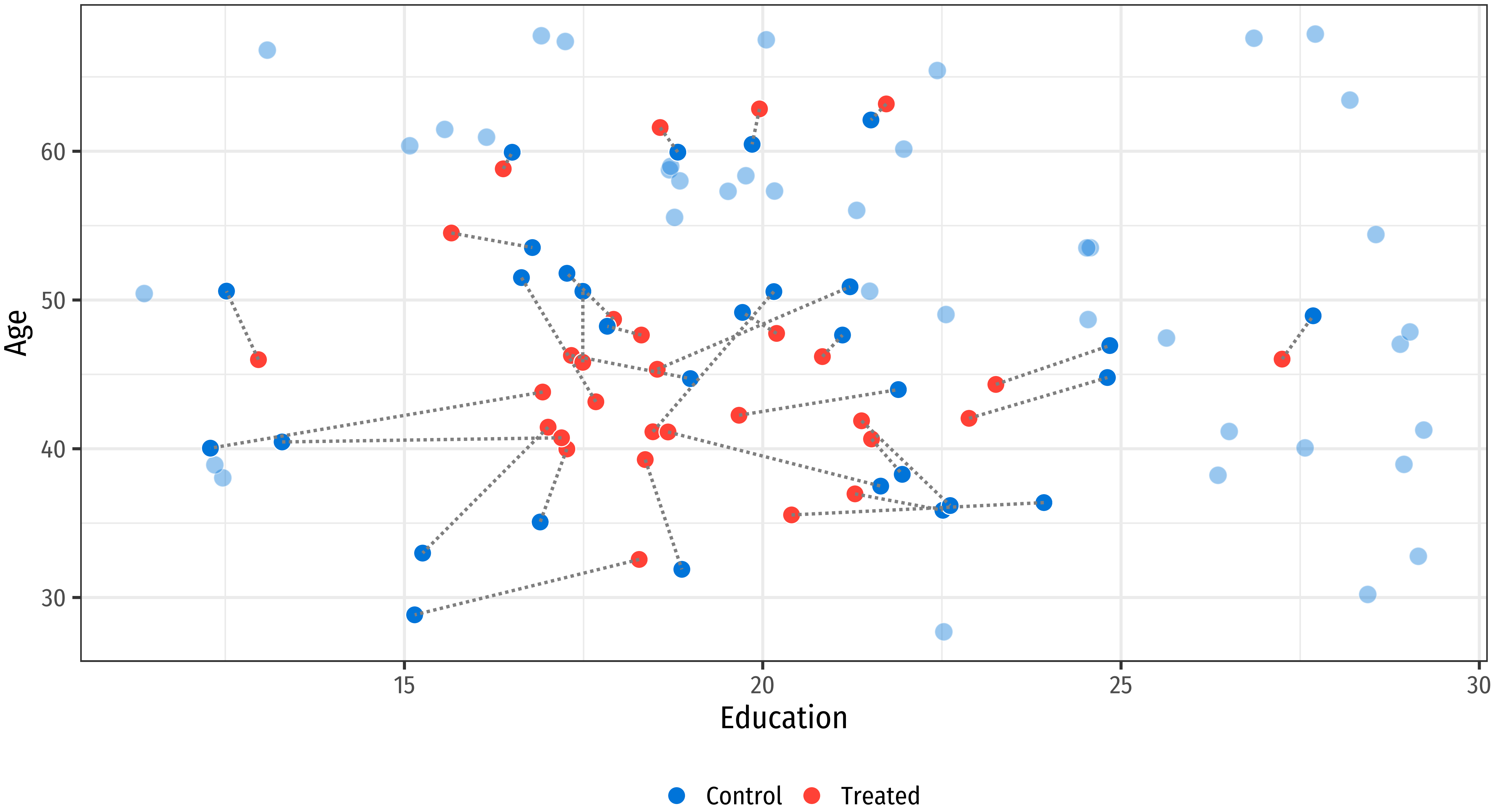
Treated



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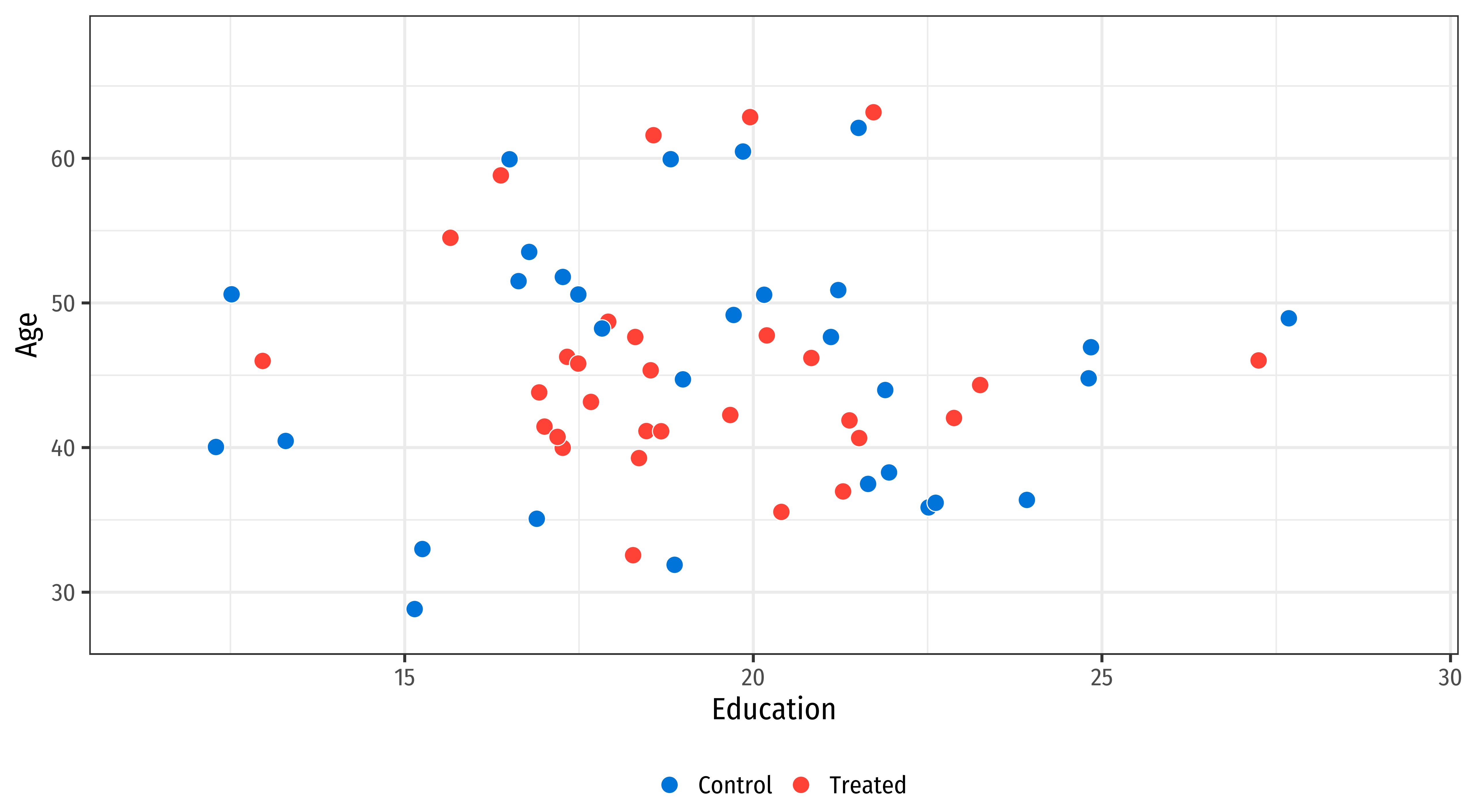
Age
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Treated

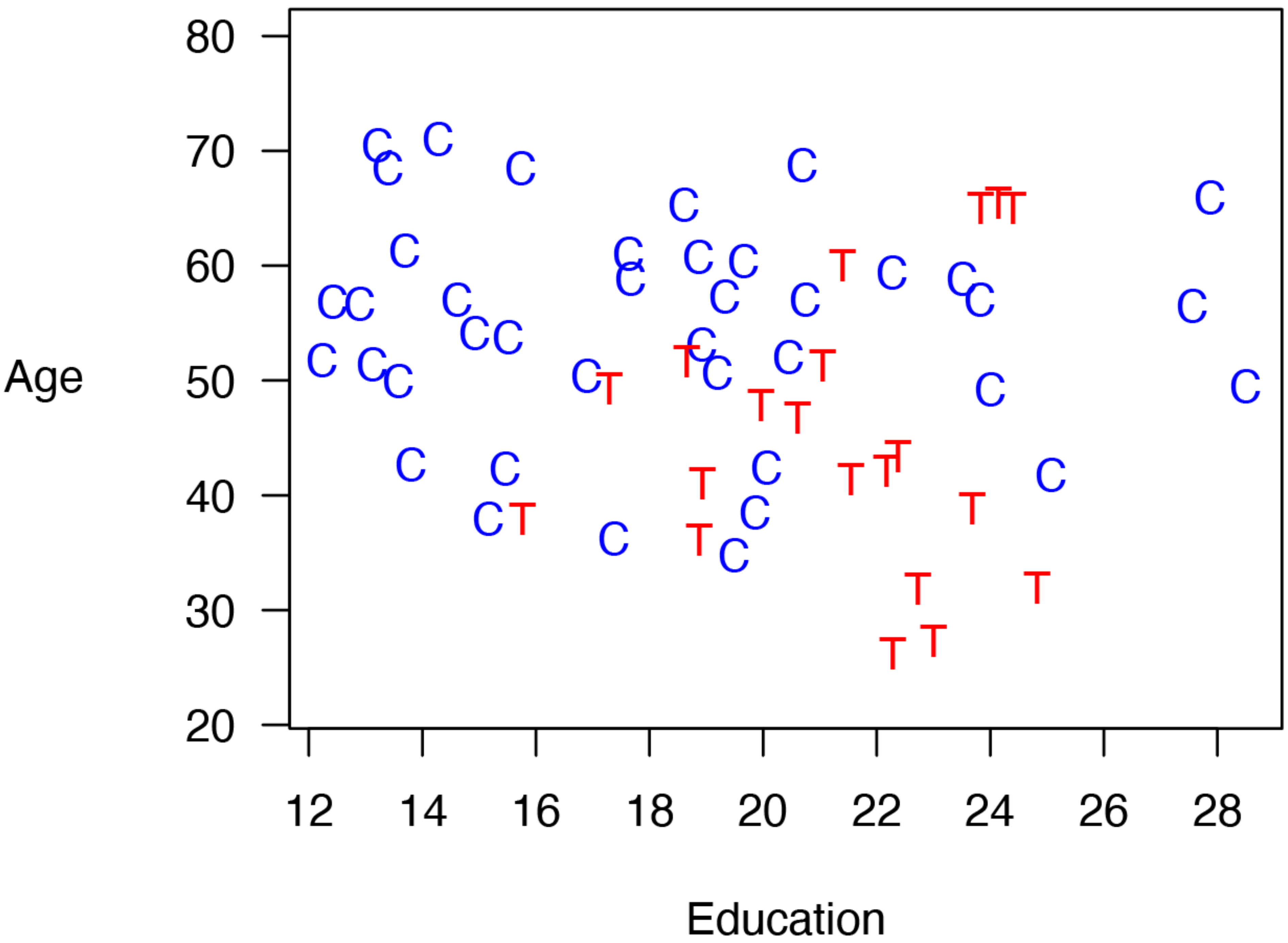
Coarsened exact matching

Use rules to partition data into clusters

Treatment should be random within clusters

Unconfoundedness again!

Some clusters will be more/less important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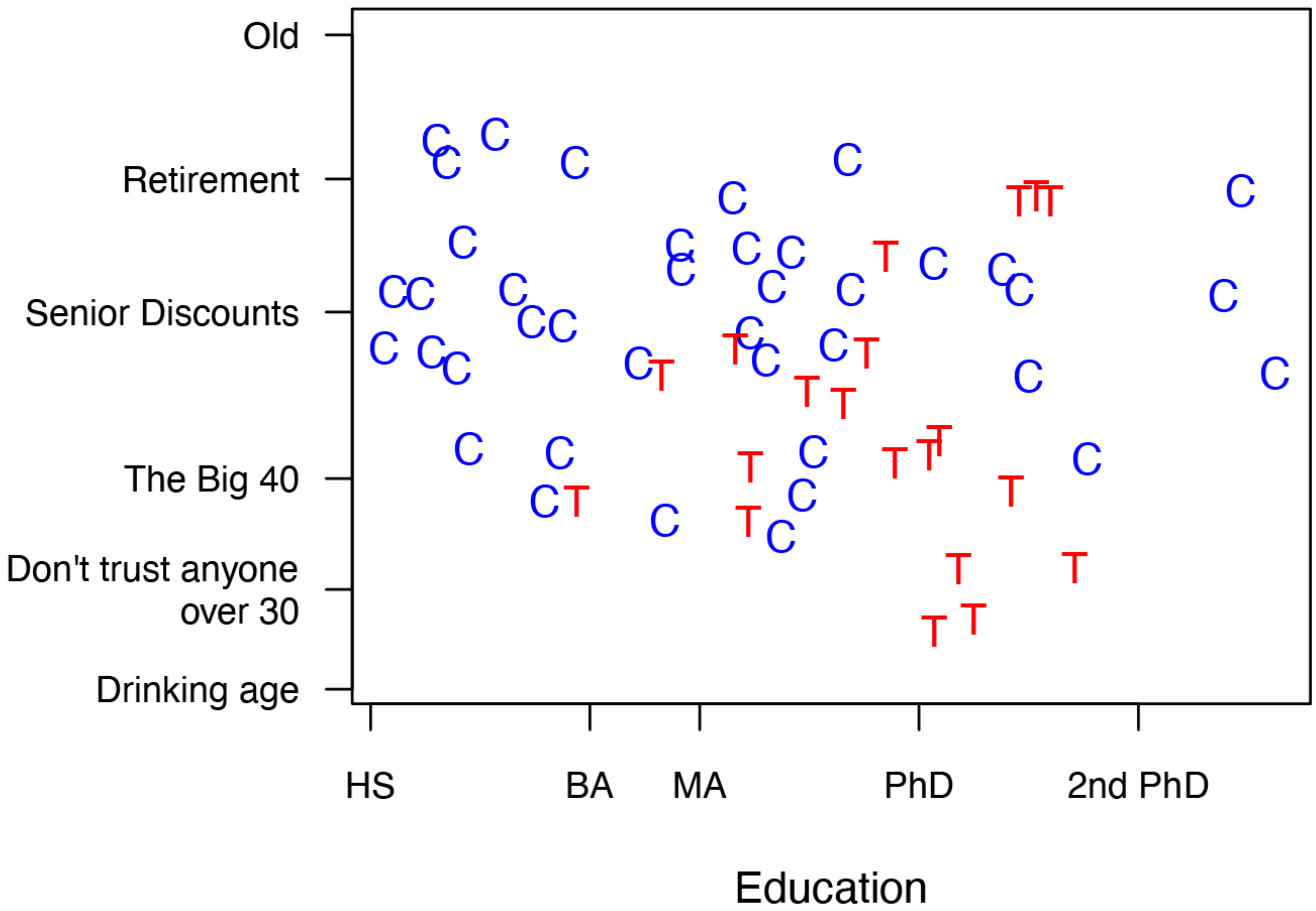
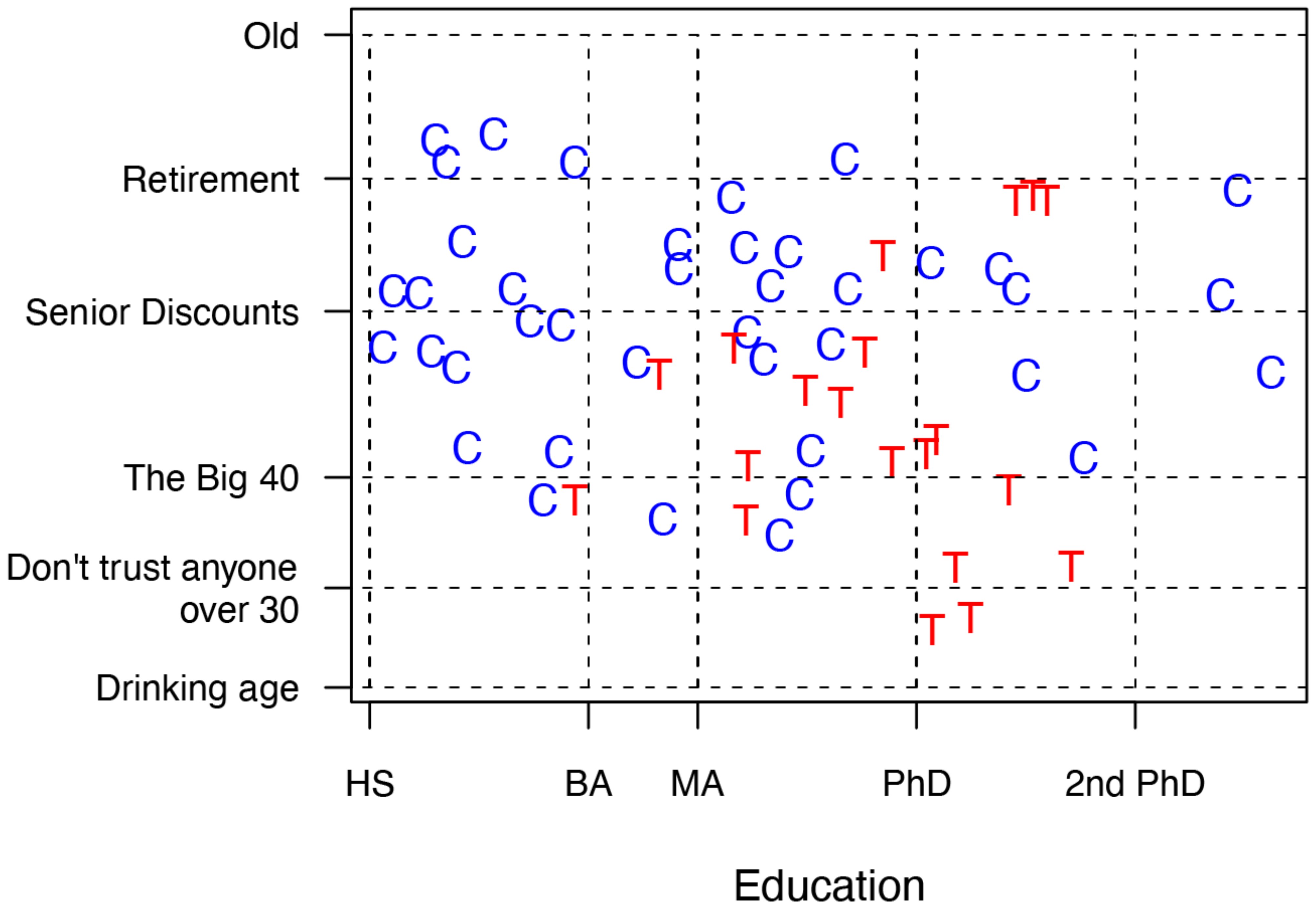

Old
Retirement
Senior Discounts
The Big 40
Don't trust anyone over 30
Drinking age
HS
BA
MA
PhD
2nd PhD
Education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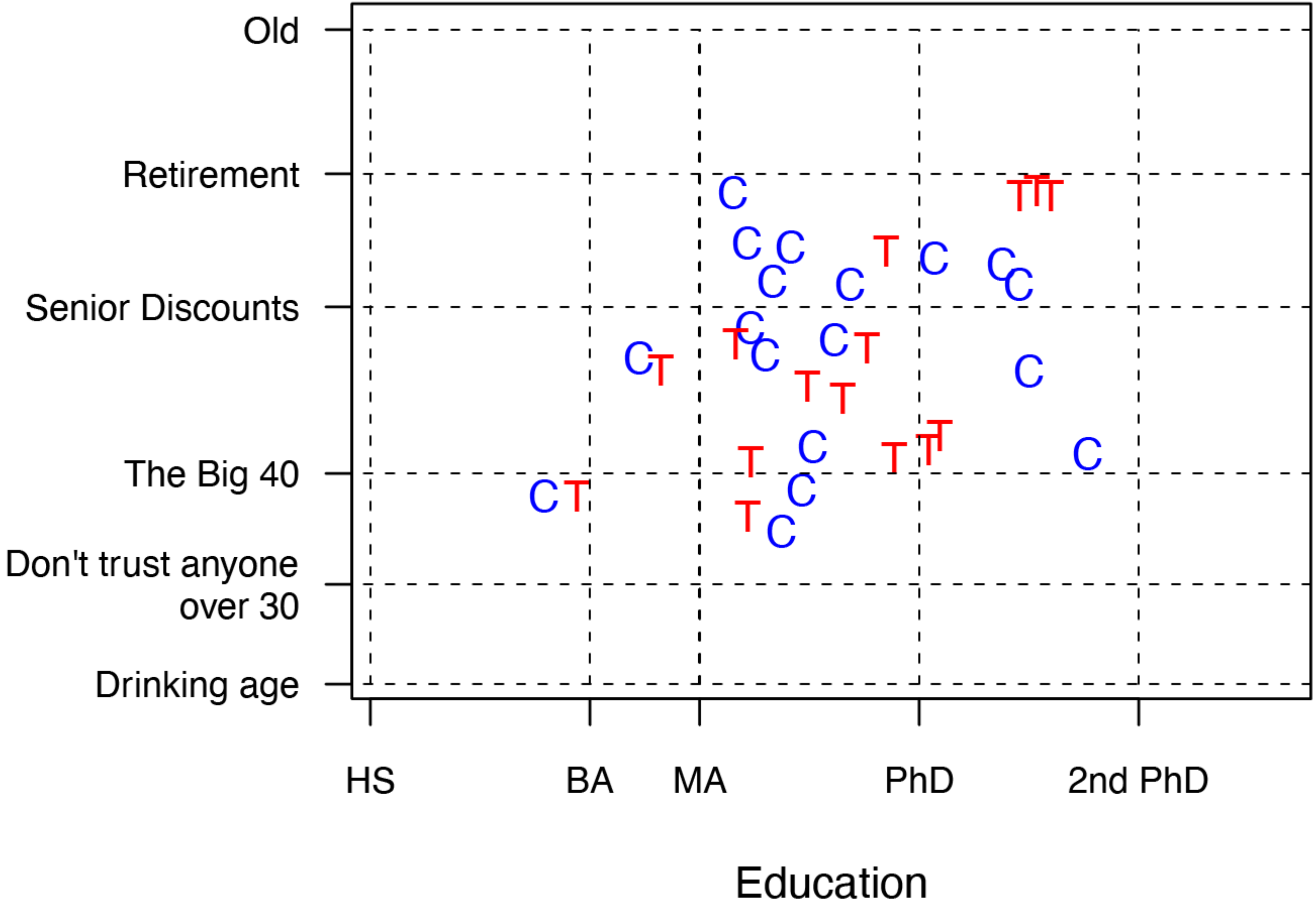
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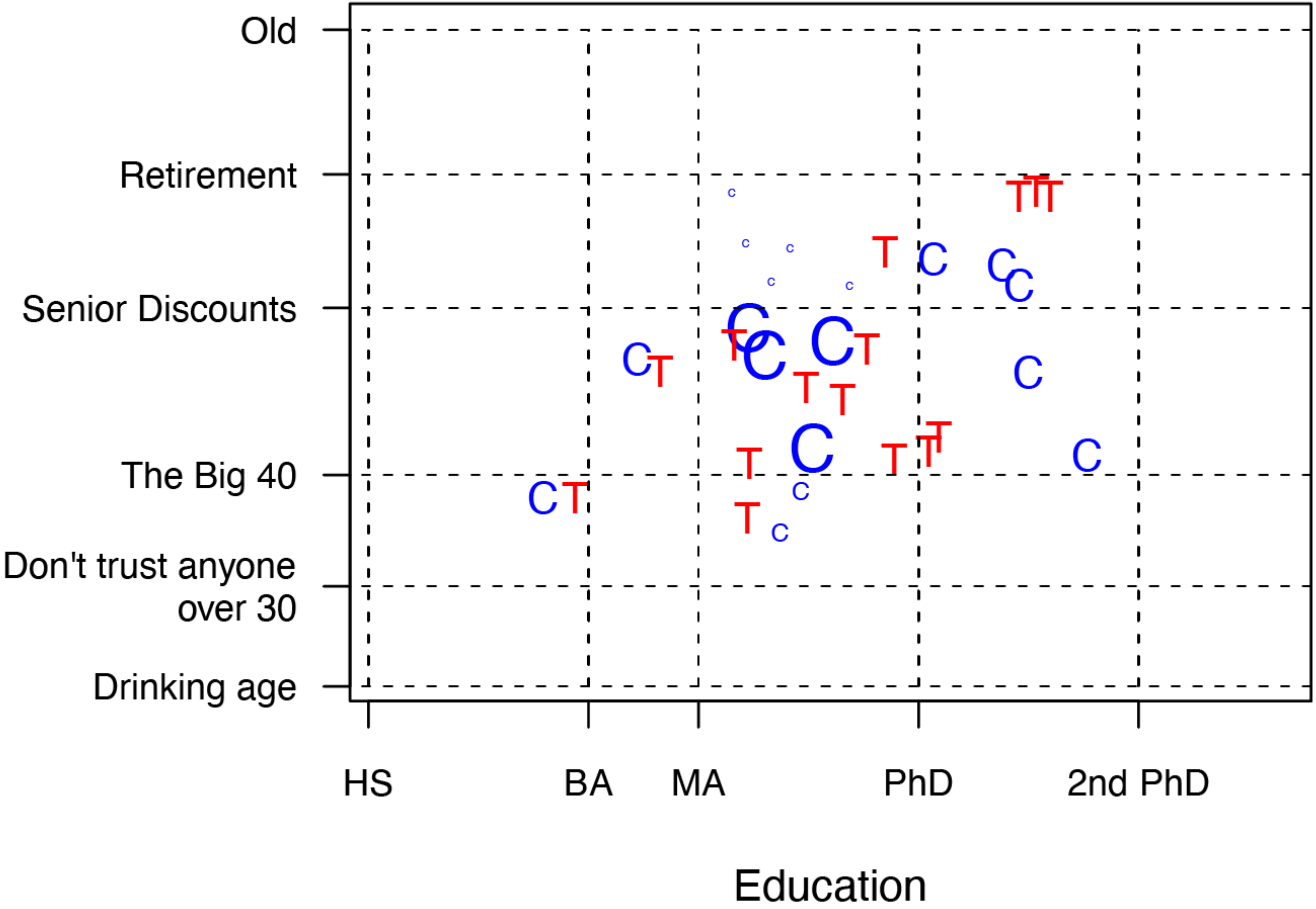

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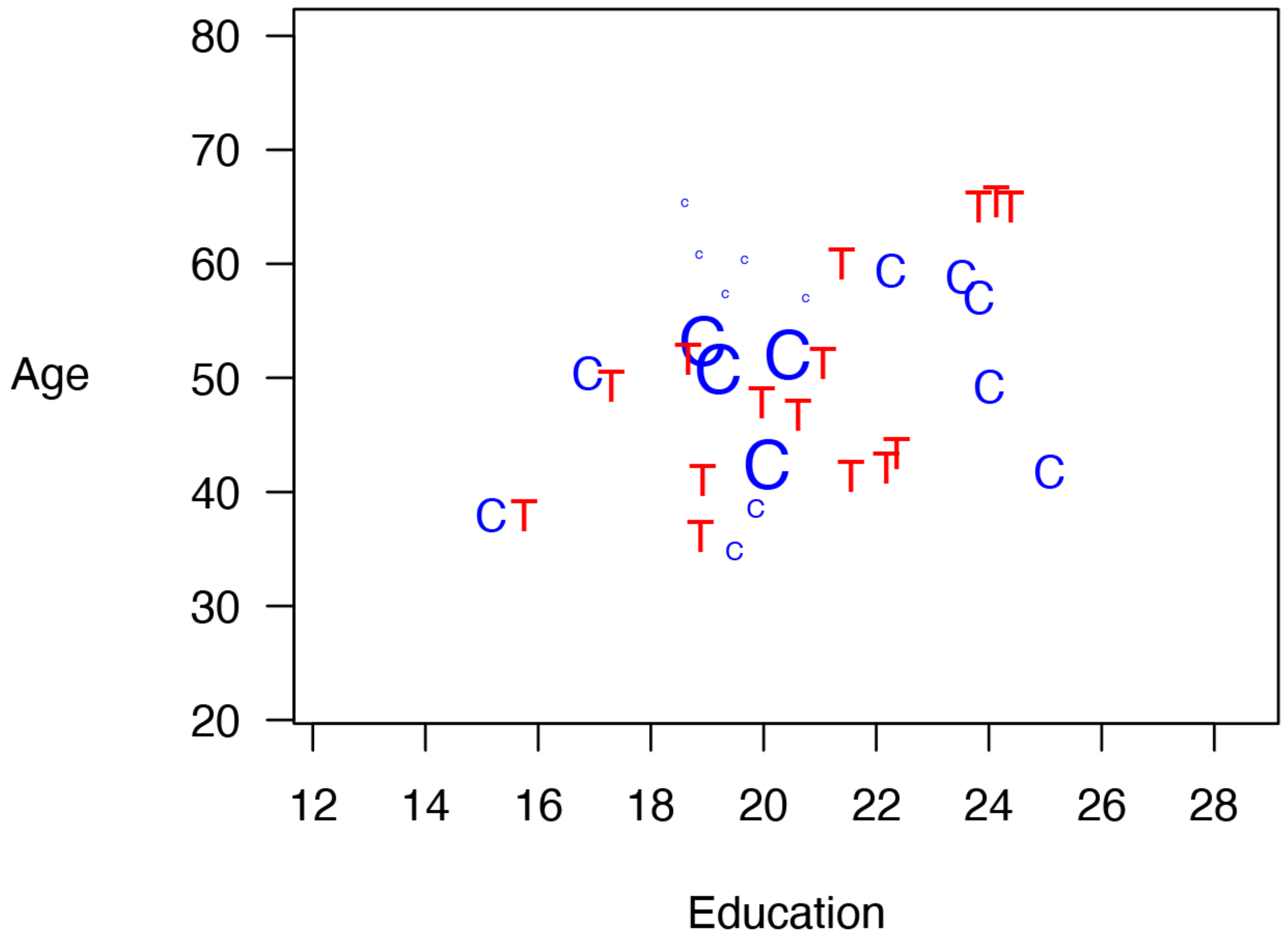

Age
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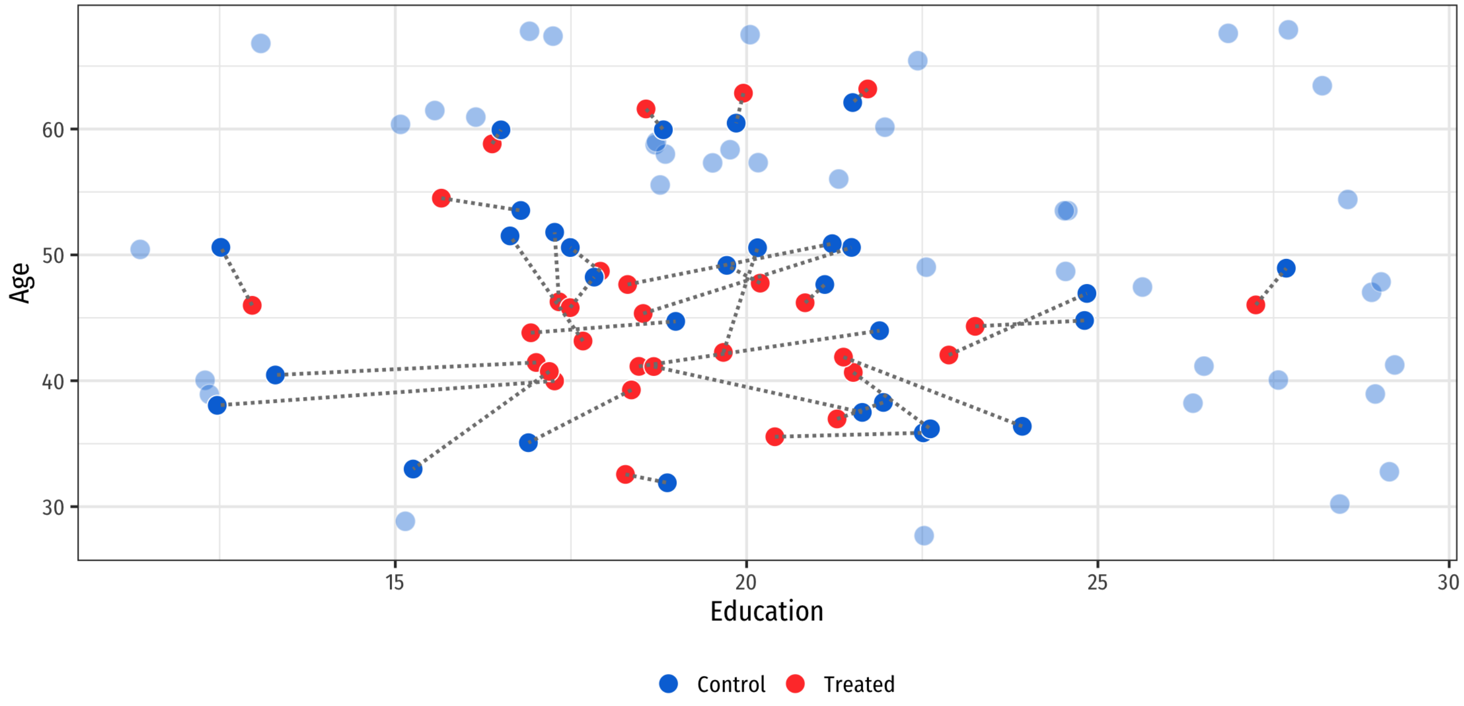
Education

Potential problems with matching

Nearest neighbor matching and CEM can be greedy!



Solution: Don't throw everything away

Propensity scores

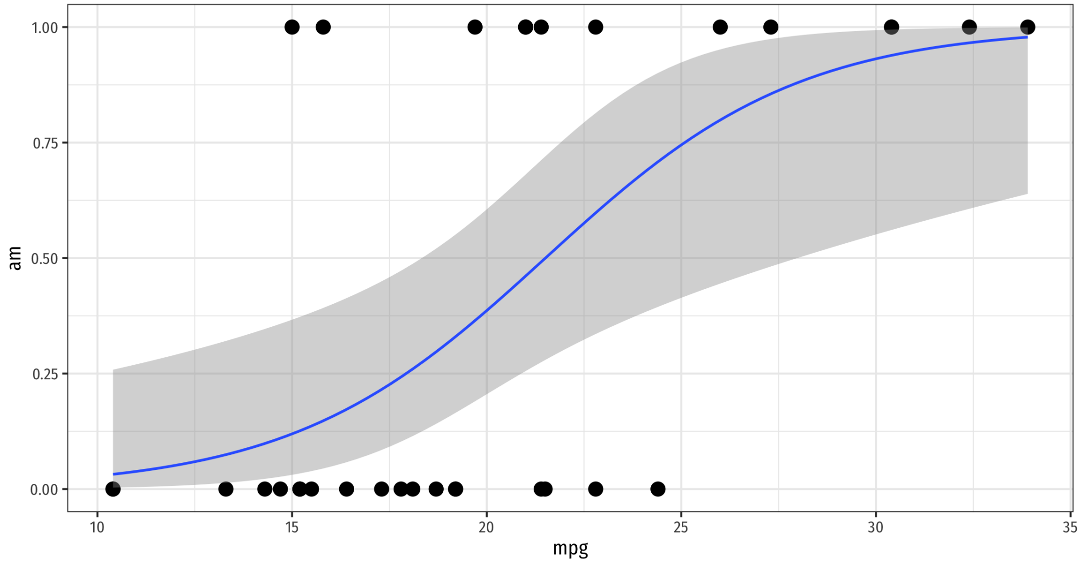
Predict the probability of assignment to treatment using a model

Logistic regression, probit regression, machine learning

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

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

```r
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!

PA

Why Propensity Scores Should Not Be Used for Matching

Gary King[1] **and Richard Nielsen**[2]

[1] *Institute for Quantitative Social Science, Harvard University, 1737 Cambridge Street, Cambridge, MA 02138, USA. Email: king@harvard.edu, URL: http://GaryKing.org*
[2] *Department of Political Science, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, 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

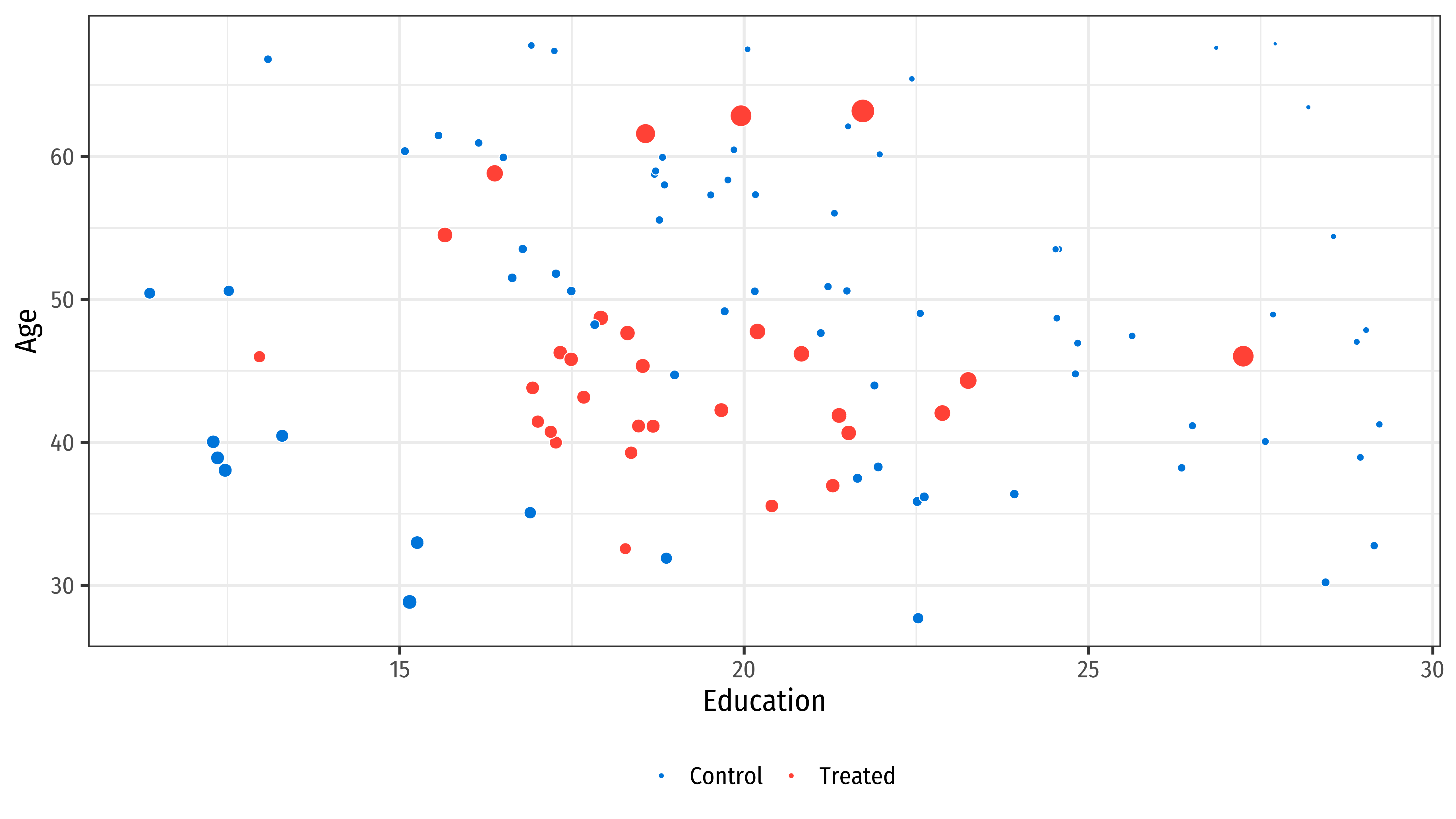
$$\frac{\text{Treatment}}{\text{Propensity}} + \frac{1 - \text{Treatment}}{1 - \text{Propensity}}$$

```r
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!



60
50
40
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Age
15
20
25
30
Education
Control
Treated

Other weights

This gets you the ATE

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

Other versions of weights

(Z = treatment;
e = propensity score)

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

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

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

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

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

R example