Causal inference

School of Cities Workshop

Rohan Alexander, 1 March 2022

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- ***Telling Stories With Data***
- ***Multilevel Regression and Poststratification: A Practical Guide and New Developments***

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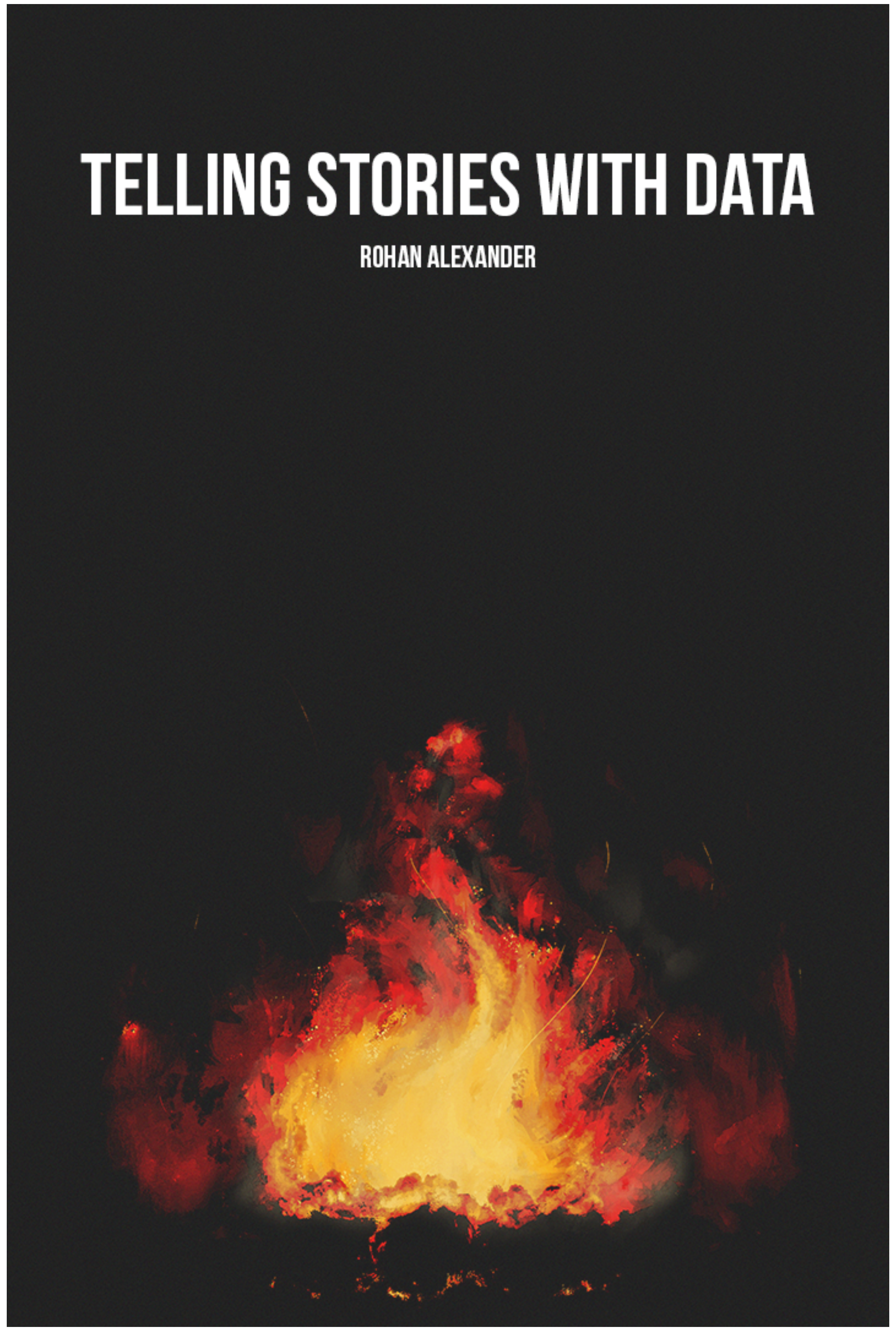

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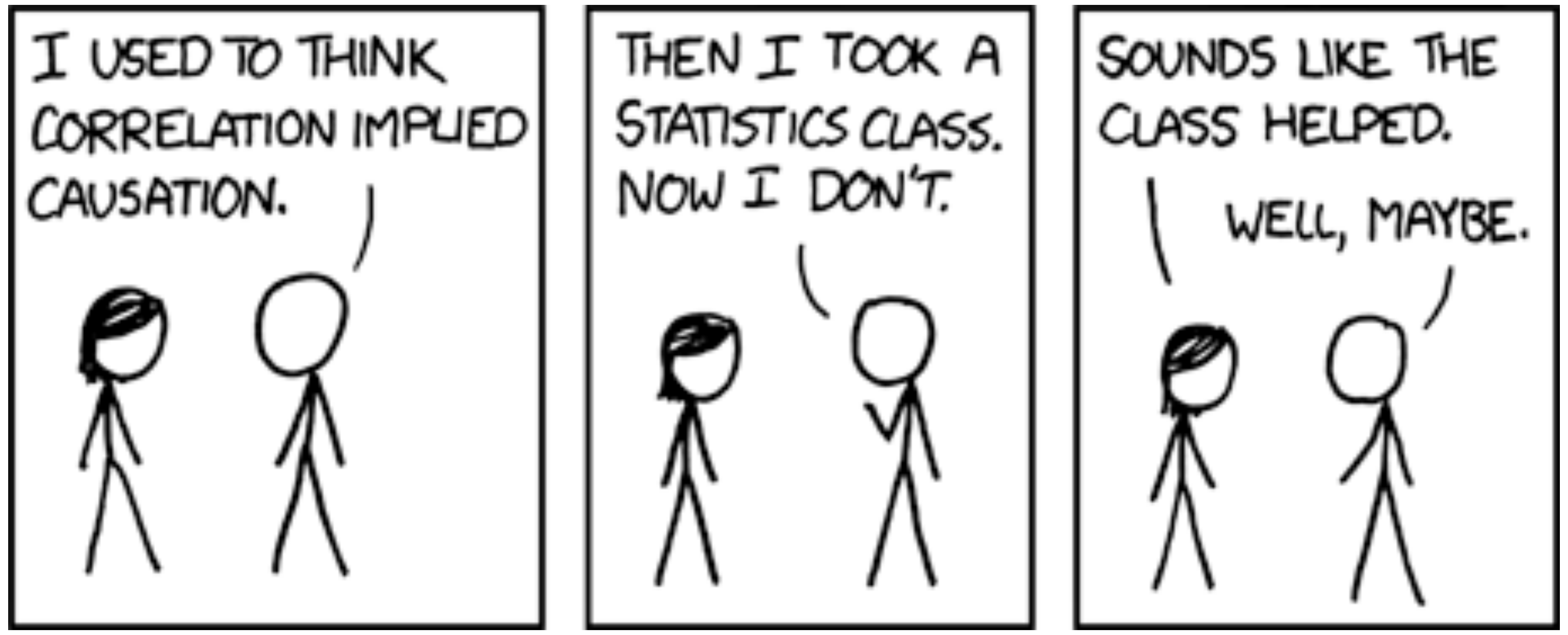
The effect?

Post hoc ergo propter hoc



https://xkcd.com/552

Causal Inference: The Mixtape, Chapter 1

Two approaches:

1. Randomization

2. Observational data

Randomization

Telling Stories with Data, Chapter 10

Please remind me to turn on the kettle

Experiments and randomized controlled trials

Fundamental problem of causal inference

The fundamental problem of causal inference:
a person cannot be both treated and untreated.

Experiments and randomized controlled trials

Neyman-Rubin model

A treatment is causal if : $(Y_i \mid t = 0) \neq (Y_i \mid t = 1)$

$$\text{ATE} = \mathbb{E}[Y \mid t = 1] - \mathbb{E}[Y \mid t = 0]\,.$$

Experiments and randomized controlled trials

Randomization

- Find a group.
- Randomly treat some of them.
- Compare outcomes.

73735	45963	78134	63873
02965	58303	90708	20025
98859	23851	27965	62394
33666	62570	64775	78428
81666	26440	20422	05720
15838	47174	76866	14330
89793	34378	08730	56522
78155	22466	81978	57323
16381	66207	11698	99314
75002	80827	53867	37797
99982	27601	62686	44711
84543	87442	50033	14021
77757	54043	46176	42391
80871	32792	87989	72248
30500	28220	12444	71840

A Million Random Digits with 100,000 Normal Deviates

Let's drink tea

Eight cups: four milk-first, four milk-last

Randomize order

Ask a taster to group them.

$$\binom{8}{4} = \frac{8!}{4!(8-4)!} = 70 \text{ possible outcomes.}$$

$$\frac{2}{70} \approx 0.028 \text{ or about 3 per cent.}$$

Causality from observational data

Telling Stories with Data, Chapter 15

1. Directed acyclic graphs
2. Two common paradoxes
3. Difference in differences

Directed acyclic graphs

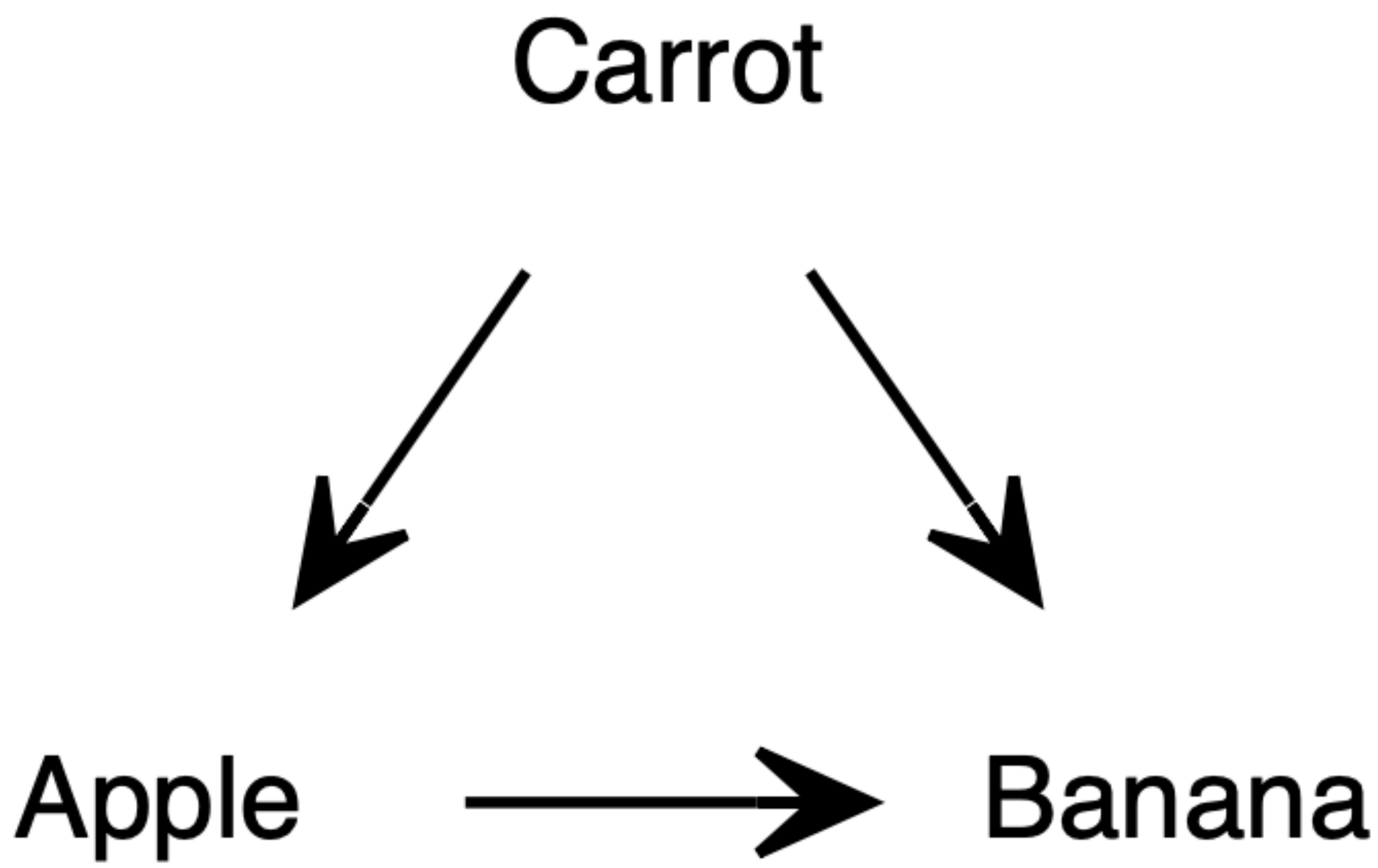
1. Confounders
2. Mediator
3. Collider

Directed acyclic graphs

A tool to be specific about our thinking

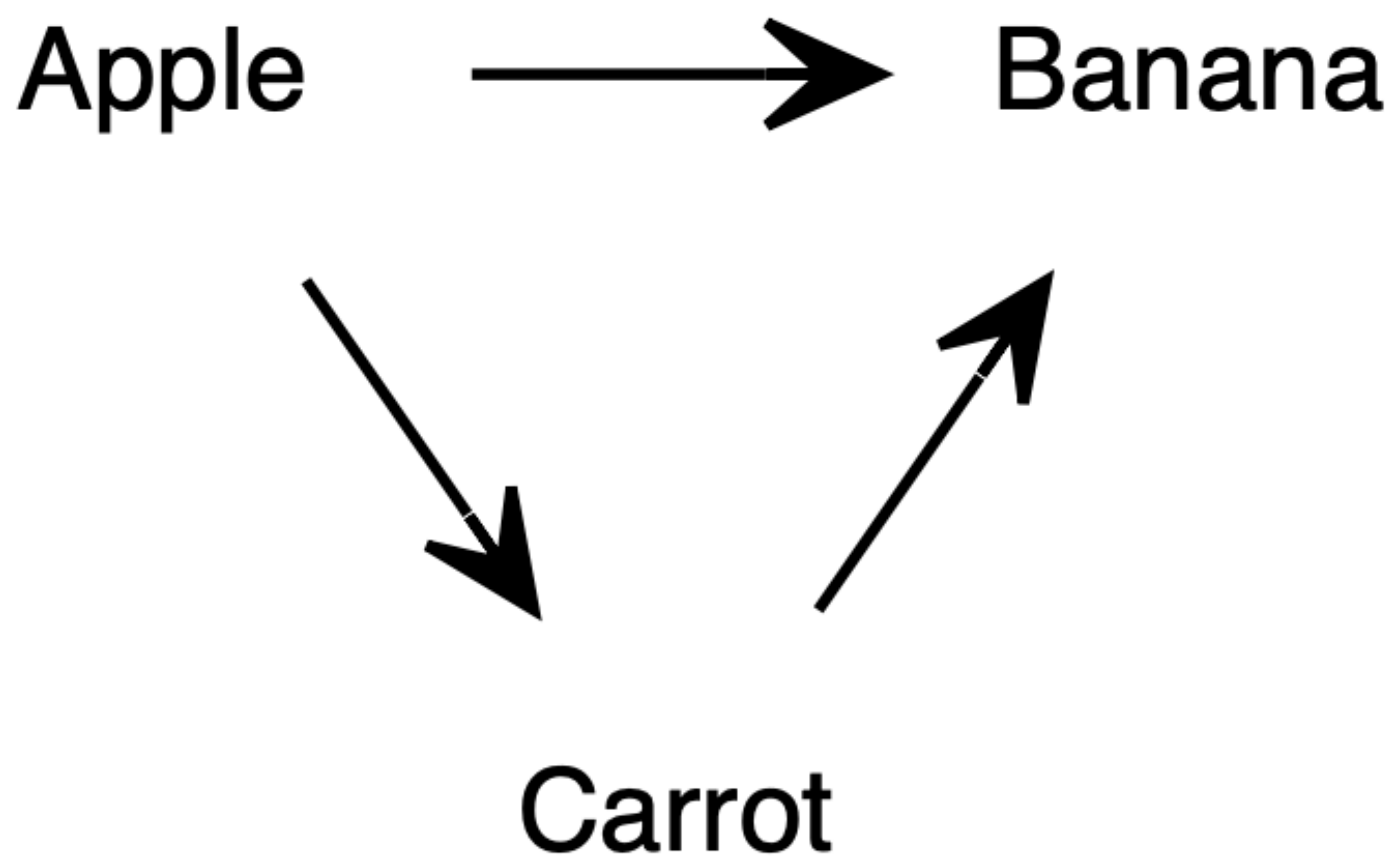
Cofounders

A DAG showing Carrot as a confounder



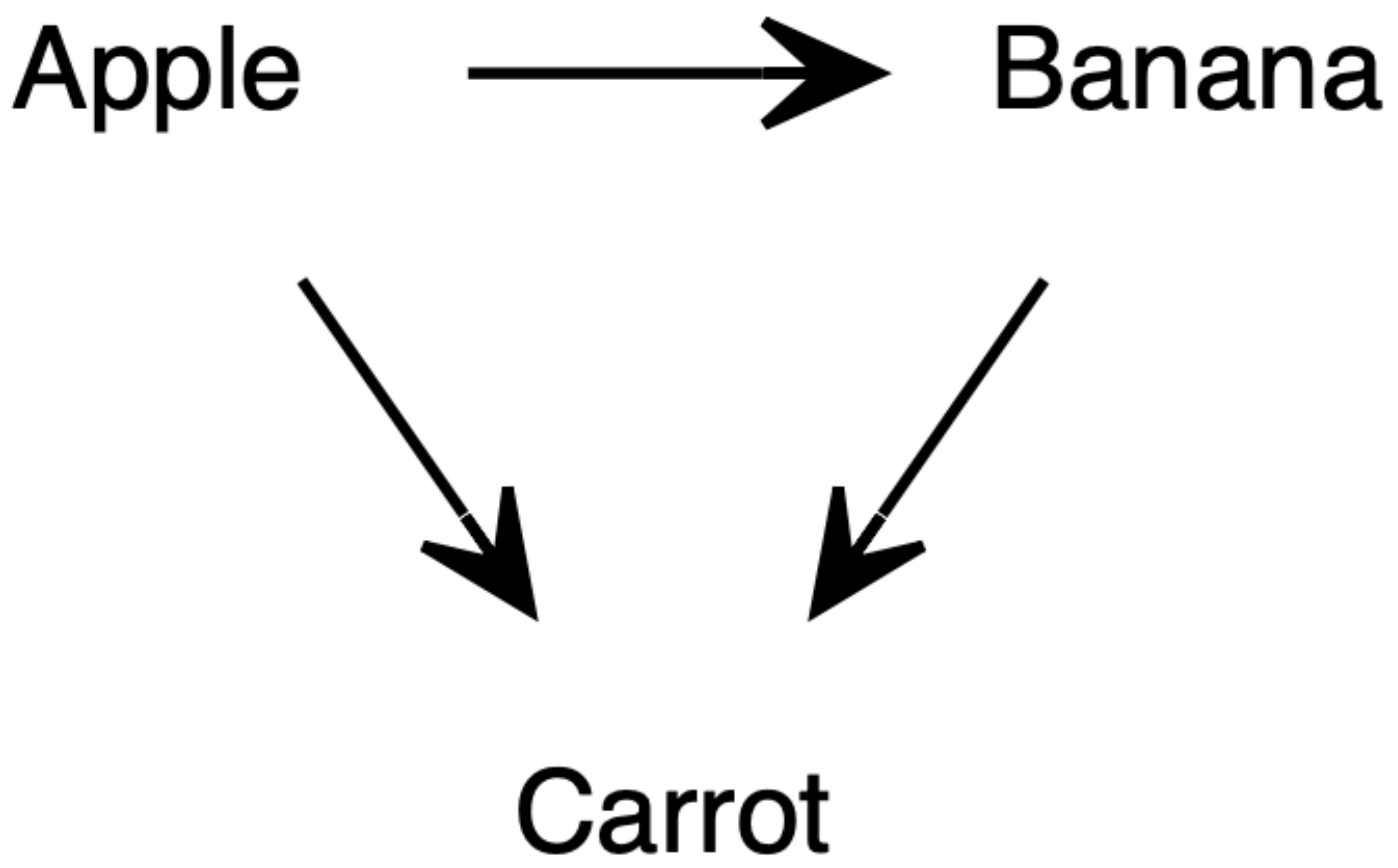
Cofounders

A DAG showing Carrot as a mediator



Cofounders

A DAG showing Carrot as a collider



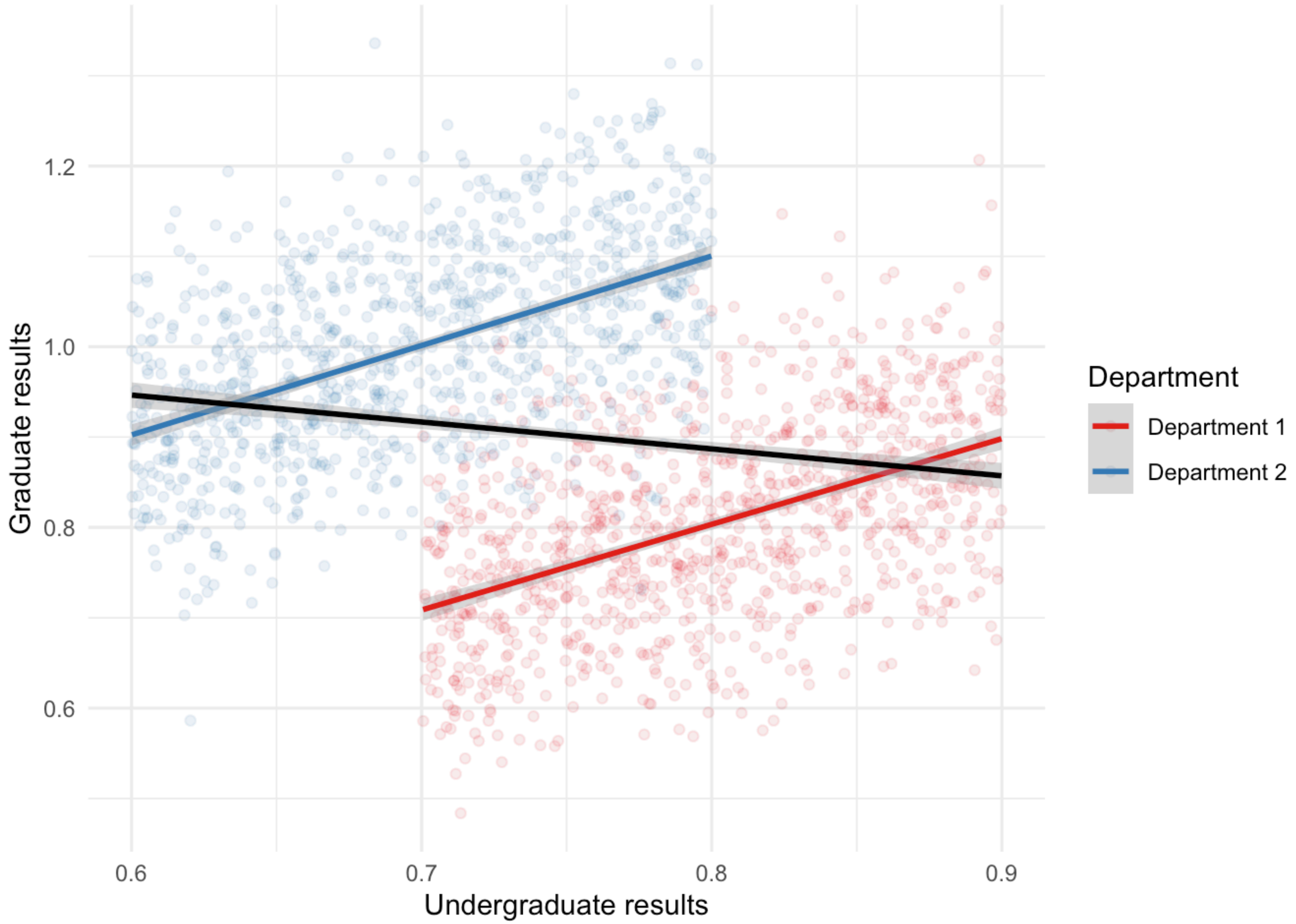
Daggy Dads or daggy DAGs?

Two common paradoxes

1. Simpson's paradox
2. Berkson's paradox

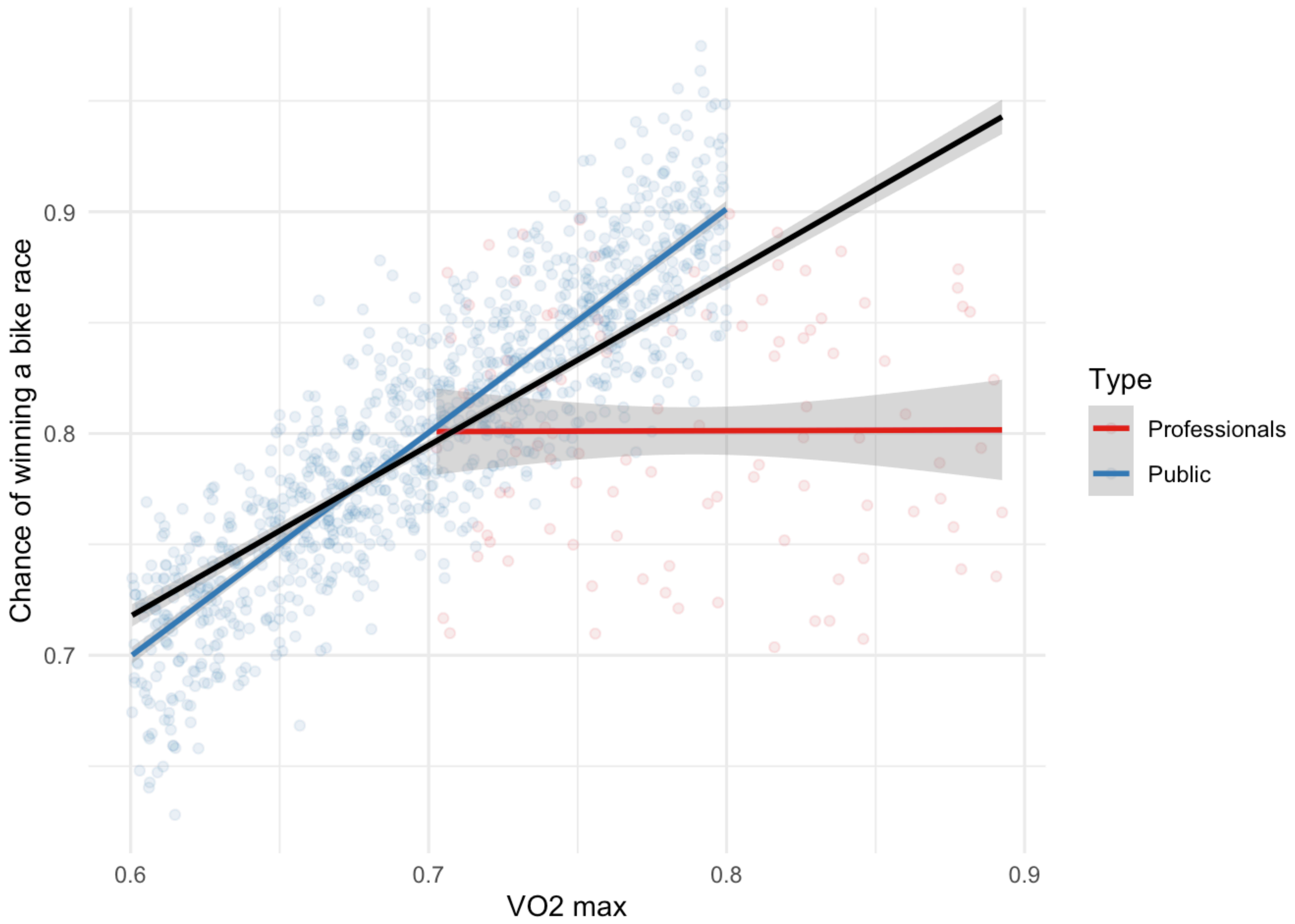
Two common paradoxes

Simpson's paradox



Two common paradoxes

Berkson's paradox



1. Difference in differences
2. Regression discontinuity
3. Instrumental variables

Should a bad tennis player blame their racket?

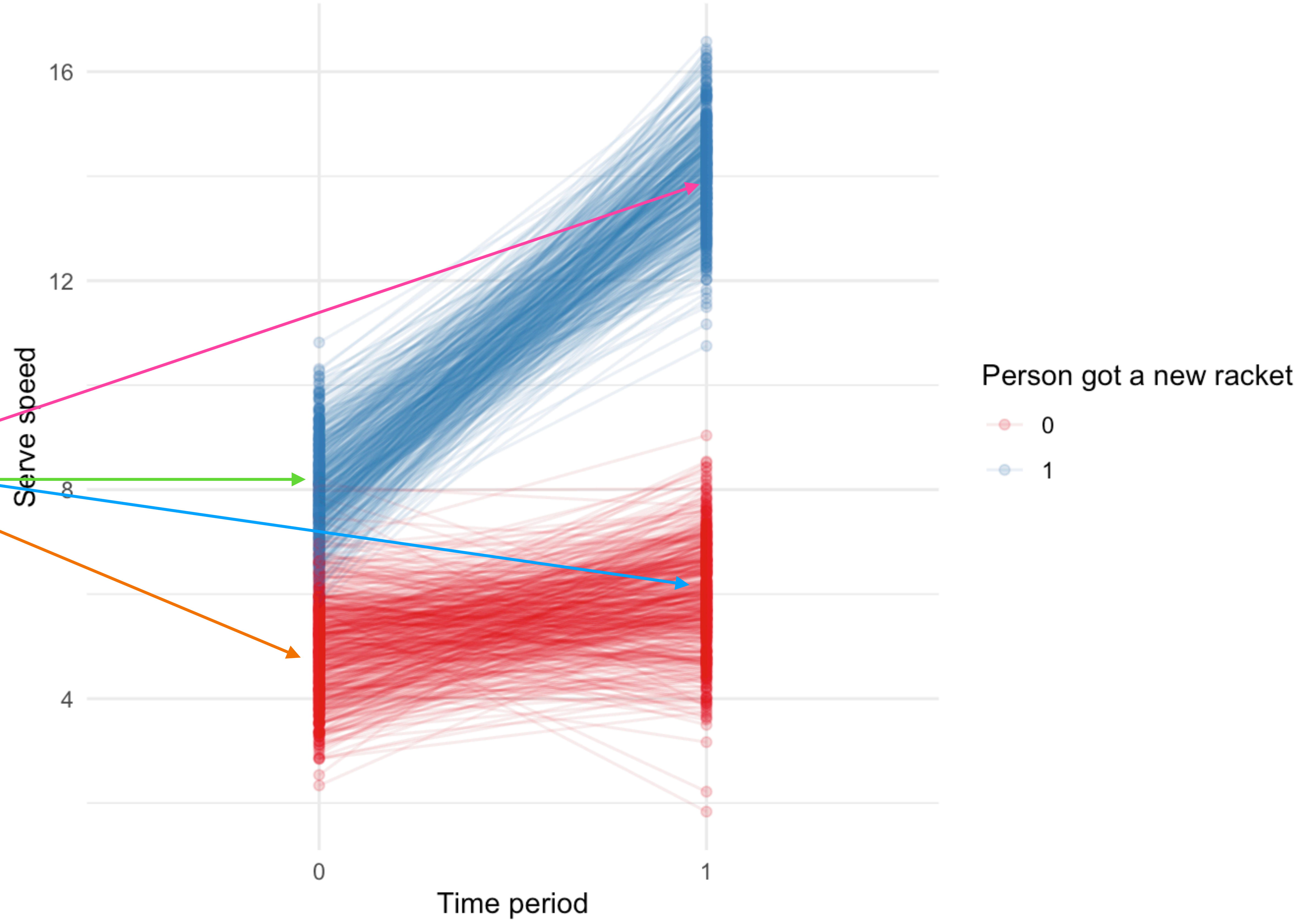
Nah, it's probably my Dad-bod's fault

- One approach:
  - Give Federer a new racket.
- Another approach:
  - Give me a new racket.
- Difference in differences

Difference in differences

Simulated data

```
simulated_difference_in_differences <-
  simulated_difference_in_differences |>
  rowwise() |>
  mutate(
    serve_speed = case_when(
      time == 0 & treatment_group == 0 ~ rnorm(n = 1, mean = 5, sd = 1),
      time == 1 & treatment_group == 0 ~ rnorm(n = 1, mean = 6, sd = 1),
      time == 0 & treatment_group == 1 ~ rnorm(n = 1, mean = 8, sd = 1),
      time == 1 & treatment_group == 1 ~ rnorm(n = 1, mean = 14, sd = 1)
    )
  )
```



Difference in differences

Estimation

Two approaches

Difference the differences

“This minus that”

```r
average_differences <-
  simulated_difference_in_differences |>
  pivot_wider(names_from = time,
              values_from = serve_speed,
              names_prefix = "time_") |>
  mutate(difference = time_1 - time_0) |>
  group_by(treatment_group) |>
  summarize(average_difference = mean(difference))

average_differences$average_difference[2] - average_differences$average_
#> [1] 5.058414
```

Linear regression with treatment binary

$$Y_{i,t} = \beta_0 + \beta_1 \text{Treatment binary}_i + \beta_2 \text{Time binary}_t + \beta_3 (\text{Treatment binary} \times \text{Time binary})_{i,t} + \epsilon_{i,t}$$

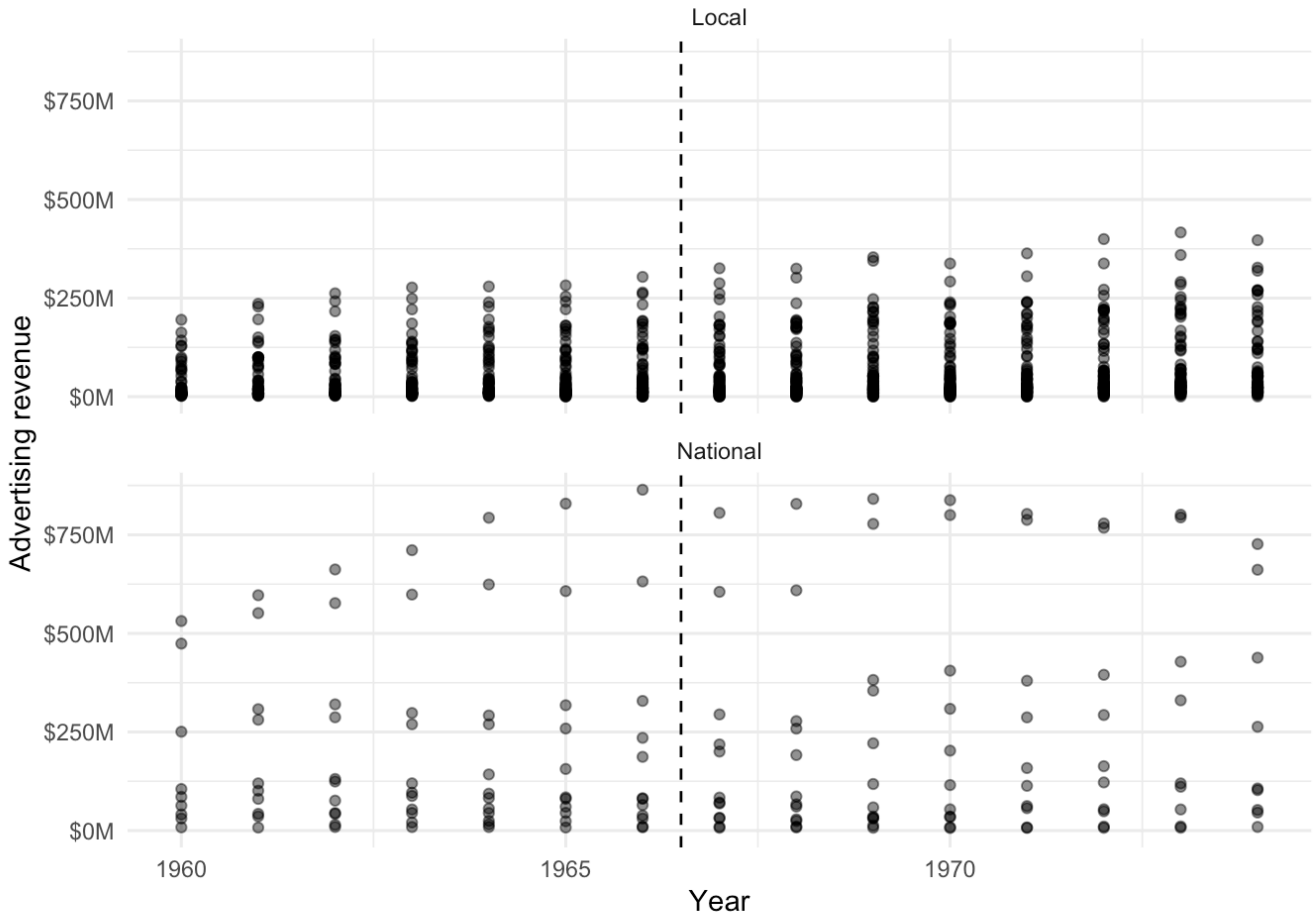
```r
diff_in_diff_example_regression <-
  lm(serve_speed ~ treatment_group*time,
     data = simulated_difference_in_differences)

summary(diff_in_diff_example_regression)
#>
#> Call:
#> lm(formula = serve_speed ~ treatment_group * time, data = simulated_d
#>
#> Residuals:
#>     Min      1Q  Median      3Q     Max
#> -4.1415 -0.6638 -0.0039  0.6708  3.2664
#>
#> Coefficients:
#>                       Estimate Std. Error t value Pr(>|t|)
#> (Intercept)            4.97131    0.04281  116.12   <2e-16
#> treatment_group1       3.03350    0.06225   48.73   <2e-16
#> time1                  1.00680    0.06055   16.63   <2e-16
#> treatment_group1:time1 5.05841    0.08803   57.46   <2e-16
```

Assumptions

- Non-parallel trends.
- Compositional differences.
- Long-term effects compared with reliability.
- Functional form dependence.

Case study: Angelucci and Cagé (2019)

French newspaper prices between 1960 and 1974



Case study: Angelucci and Cagé (2019)

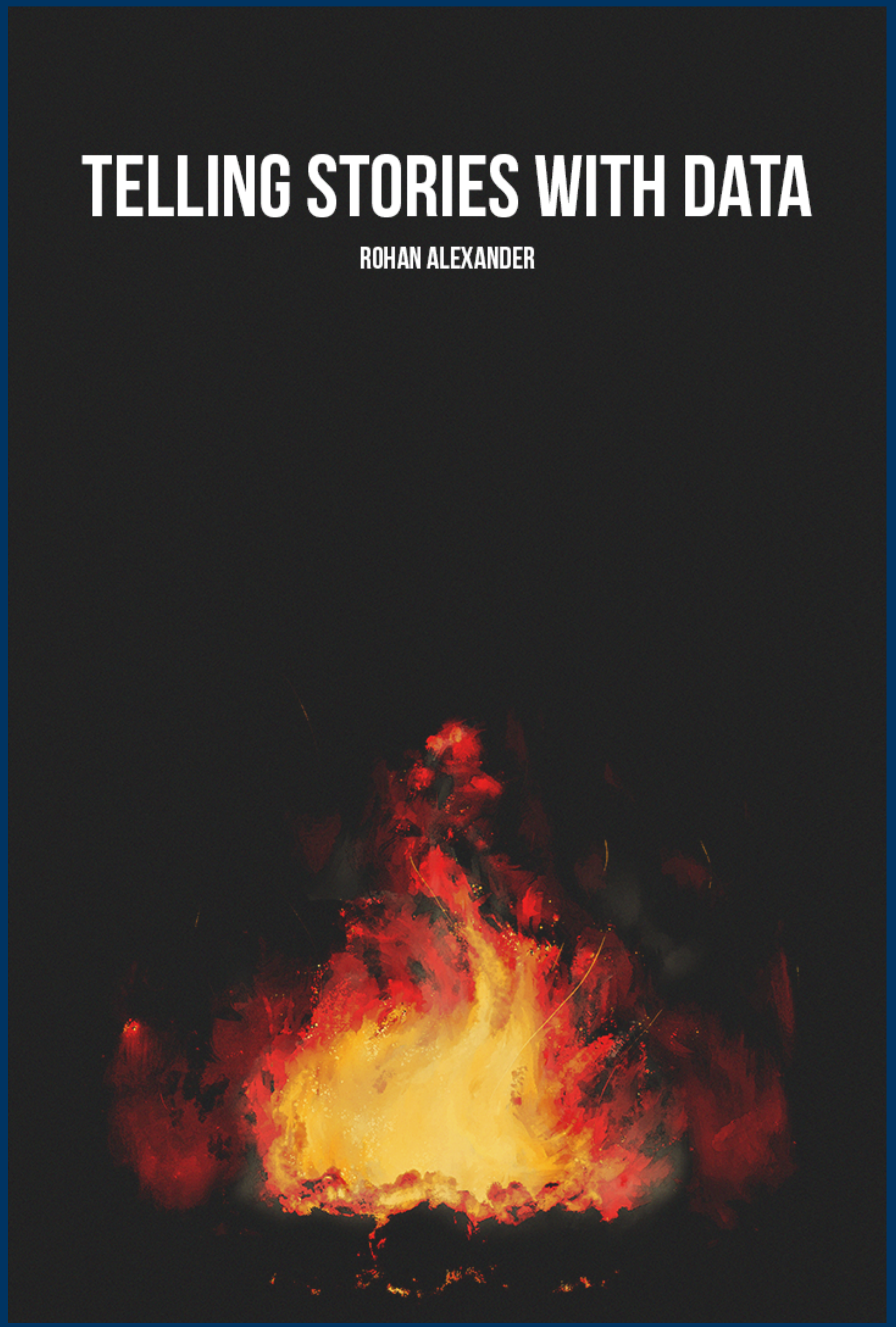
Effect of changed television advertising laws on revenue of French newspapers (1960-1974)

$$\ln(y_{n,t}) = \beta_0 + \beta_1(\text{National binary} \times \text{1967 onward binary}) + \lambda_n + \gamma_y + \epsilon.$$

	Ad revenue	Ad revenue over circulation	Ad prices	Ad space
Year	0.05	0.04	0.04	0.02
	(0.00)	(0.00)	(0.00)	(0.00)
Is after advertising change	−0.23	−0.15	−0.31	0.01
	(0.03)	(0.03)	(0.07)	(0.05)
Num.Obs.	1052	1048	809	1046
R2	0.985	0.903	0.892	0.720
R2 Adj.	0.984	0.895	0.882	0.699
AIC	−526.7	−735.0	705.4	478.0
BIC	−120.1	−328.8	1057.6	849.5
Log.Lik.	345.341	449.524	−277.714	−164.012
F	814.664	112.259	83.464	34.285

1. ~~Difference in differences~~
2. Regression discontinuity
3. Instrumental variables

Next steps



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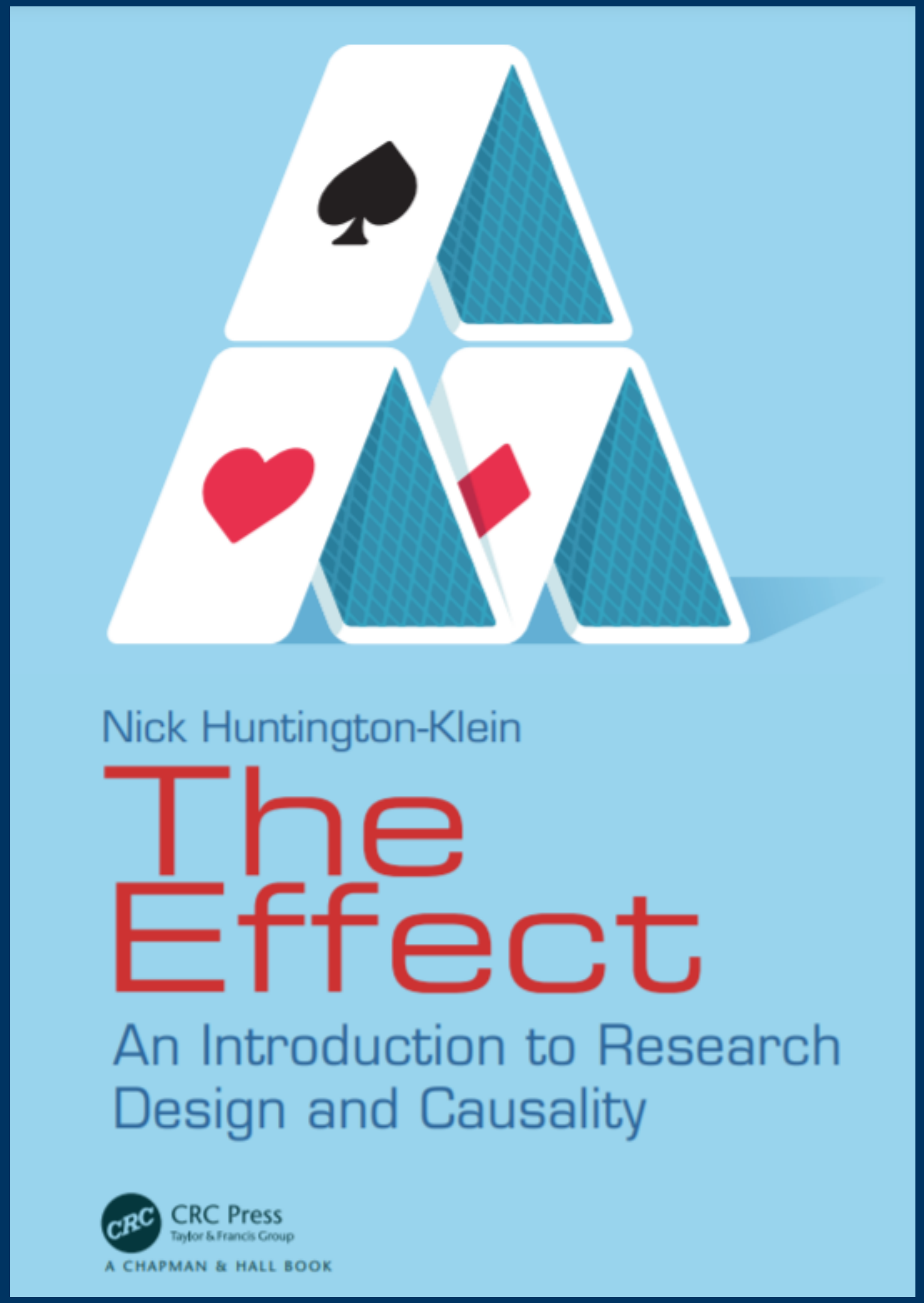
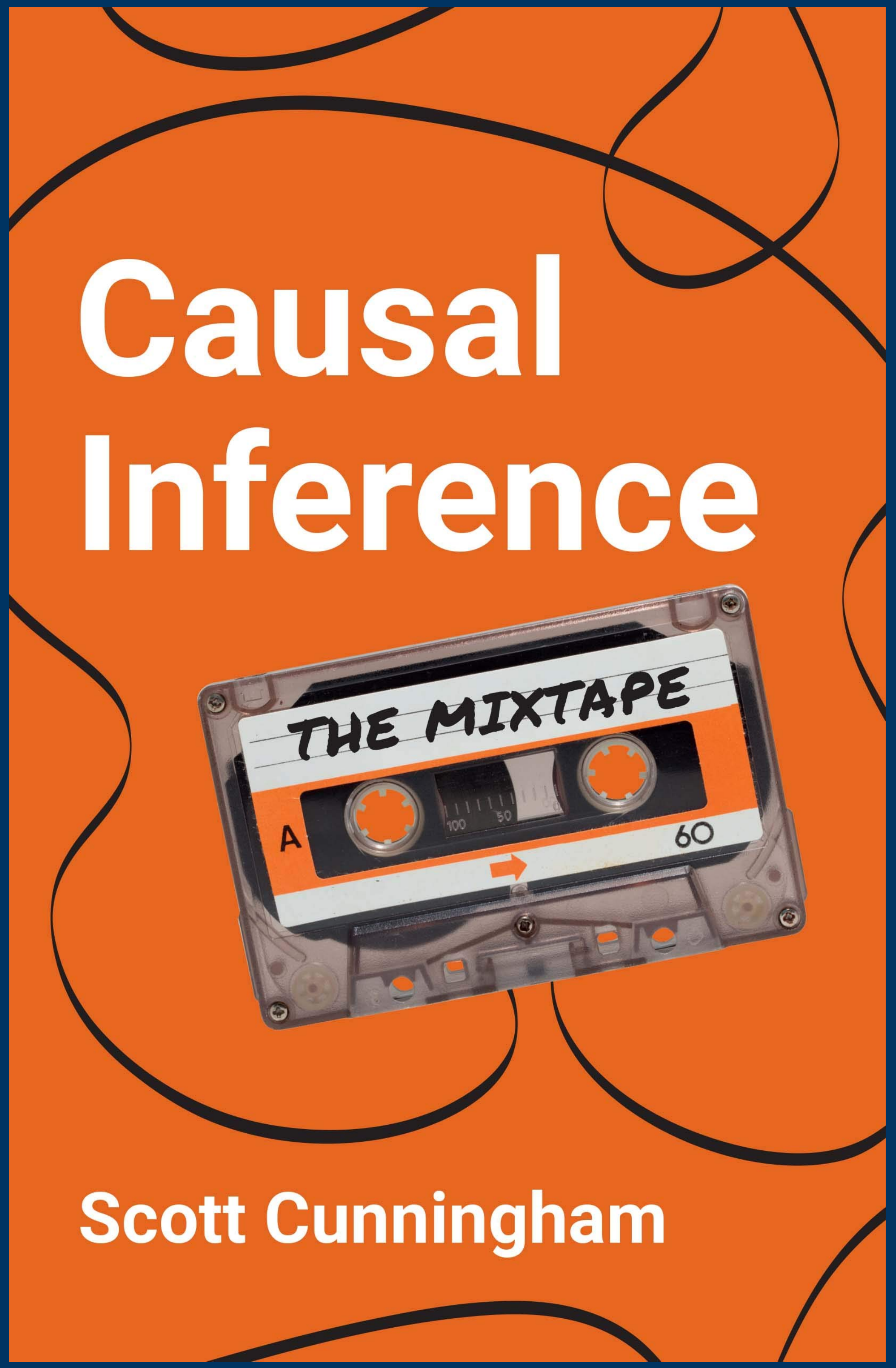


https://theeffectbook.net



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Thank you

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