In-person session 5

February 13, 2025

PMAP 8521: Program evaluation
Andrew Young School of Policy Studies

Plan for today

DAGs

Plan for today

DAGs

Logic models, DAGs, and measurement

Plan for today

DAGs

Logic models, DAGs, and measurement

Potential outcomes and do()

Plan for today

DAGs

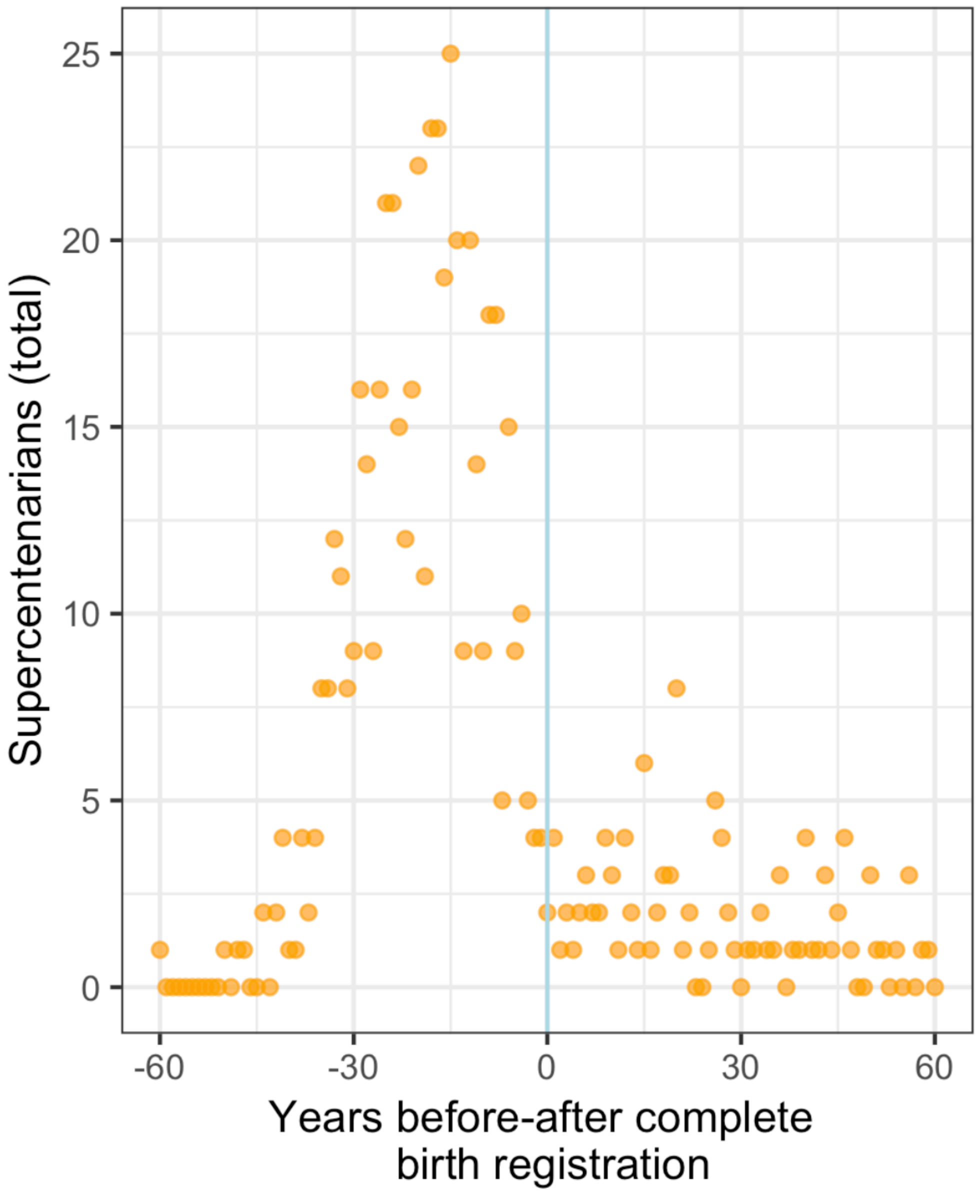
Logic models, DAGs, and measurement

Potential outcomes and do()

do-calculus and adjustment

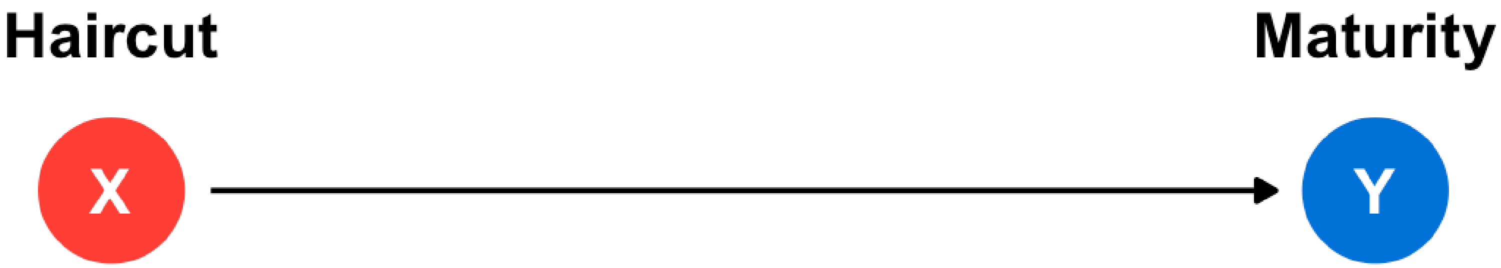
DAGs

**Causal thinking is necessary—
even for descriptive work!**


Supercentenarians (total)
25
20
15
10
5
0
-60
-30
0
30
60
Years before-after complete
birth registration

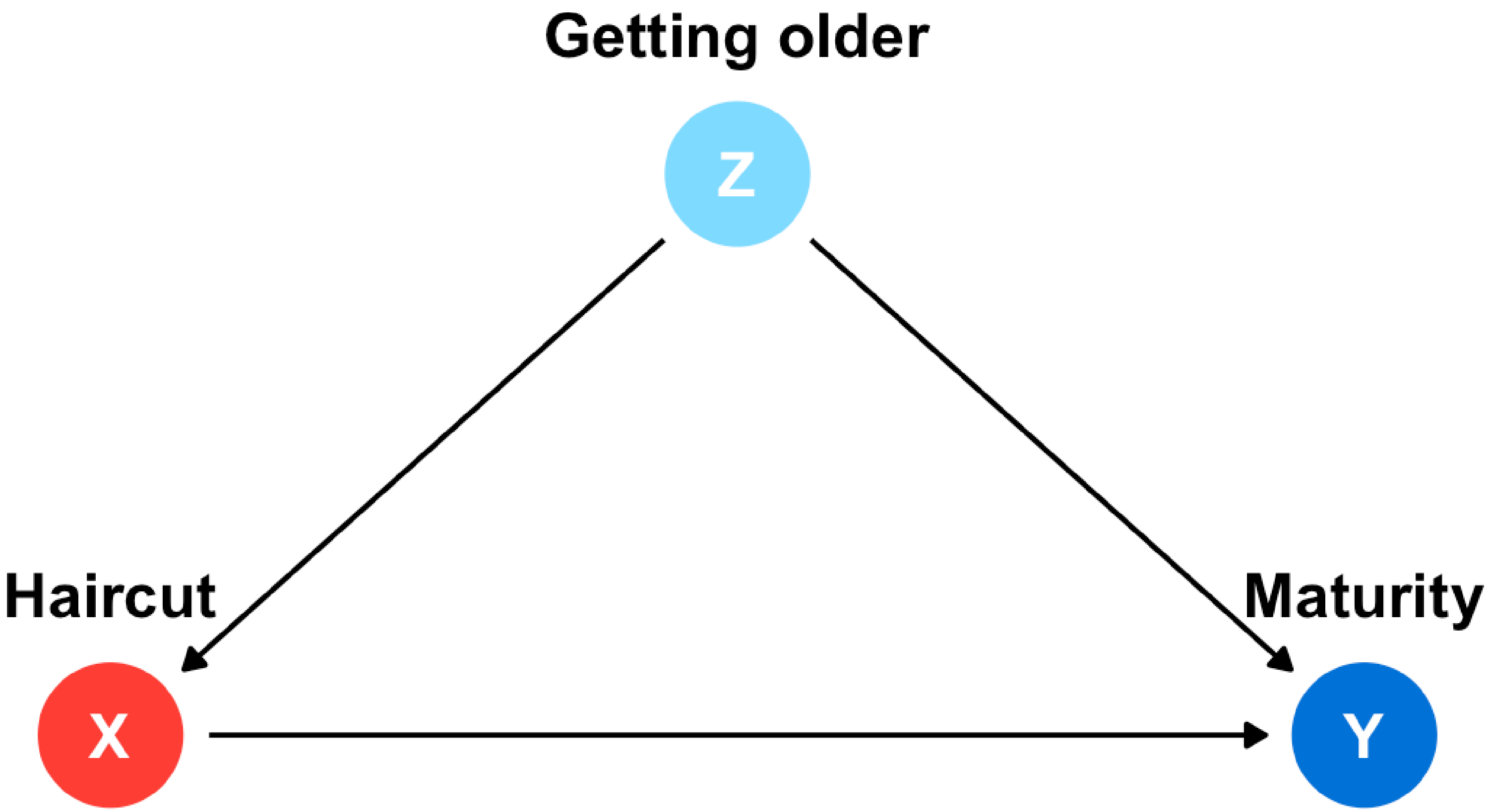
"Every time I get a haircut, I become more mature!"

"Every time I get a haircut, I become more mature!"



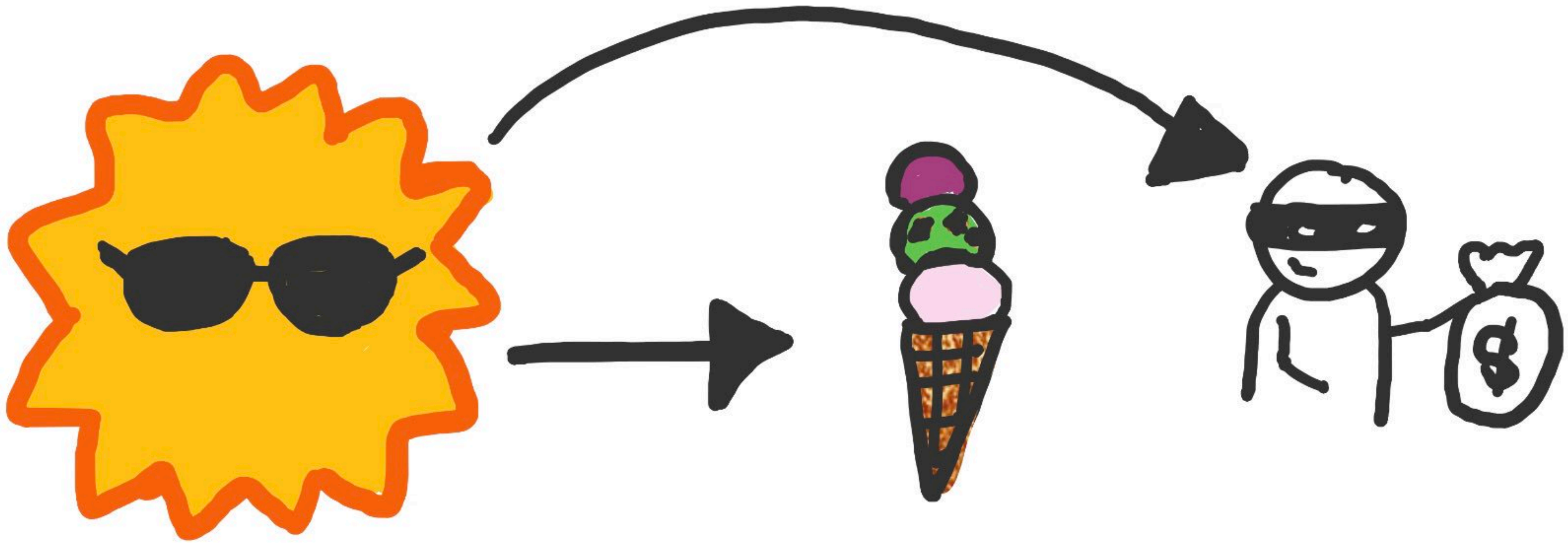
$$E[\text{Maturity} \mid \text{do}(\text{Get haircut})]$$

Getting older opens a backdoor path

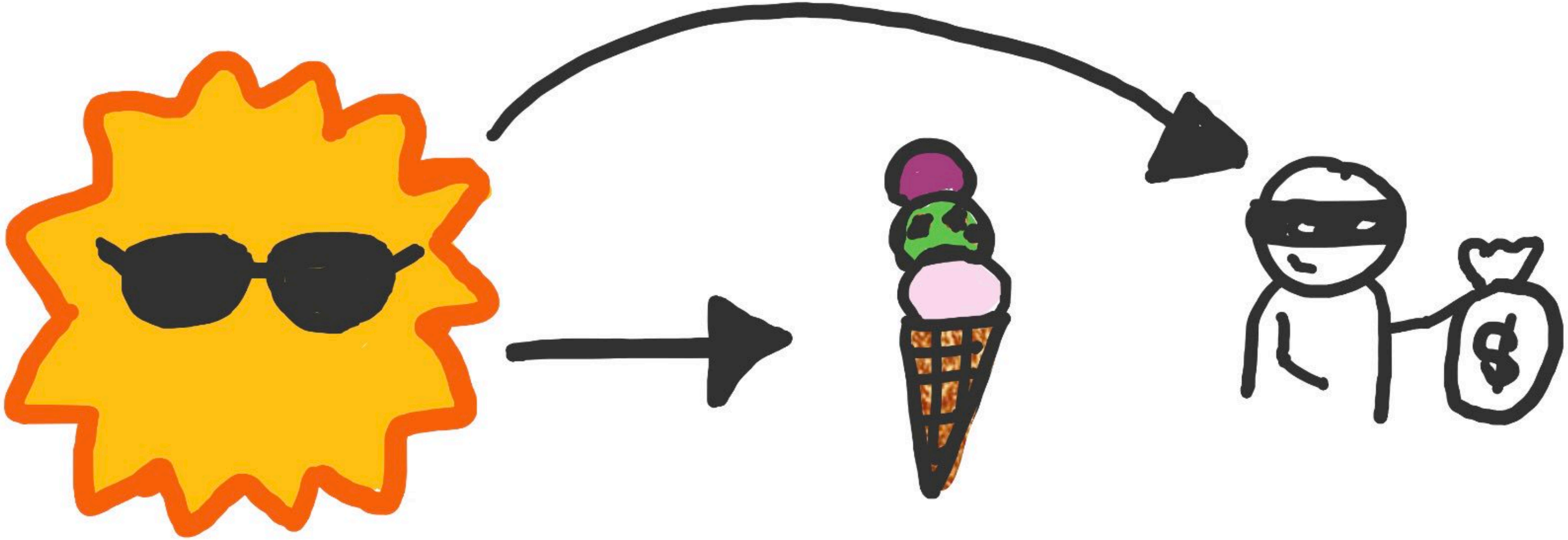


Ice cream causes crime

Ice cream causes crime



Ice cream causes crime



Summer weather opens a backdoor path

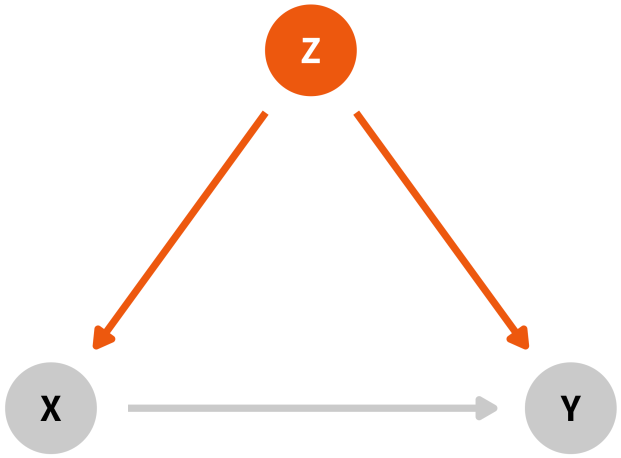
But what does that mean, "opening a backdoor path"?

How does statistical association get passed through paths?

How do I know which of these is which?

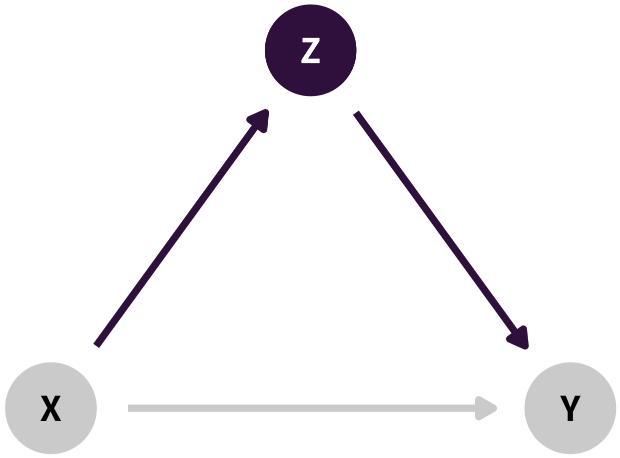
Confounder

(Fork)



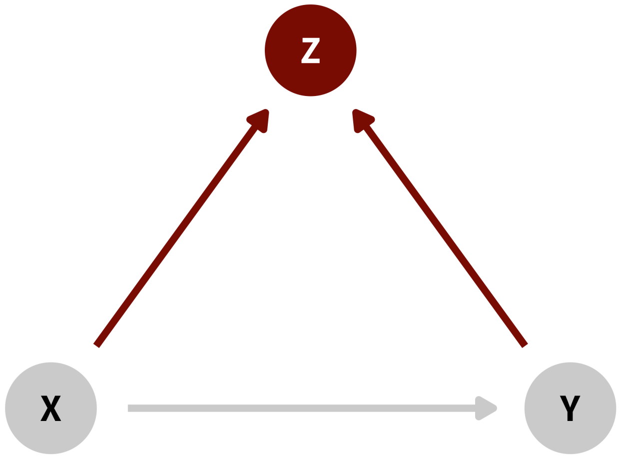
Mediator

(Chain)

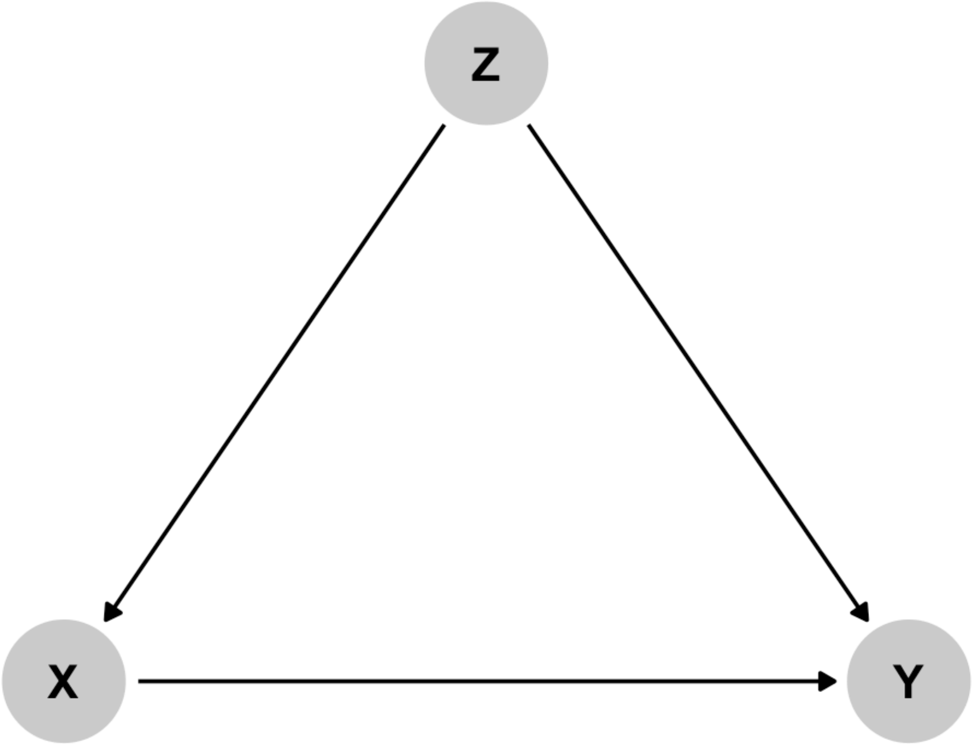


Collider

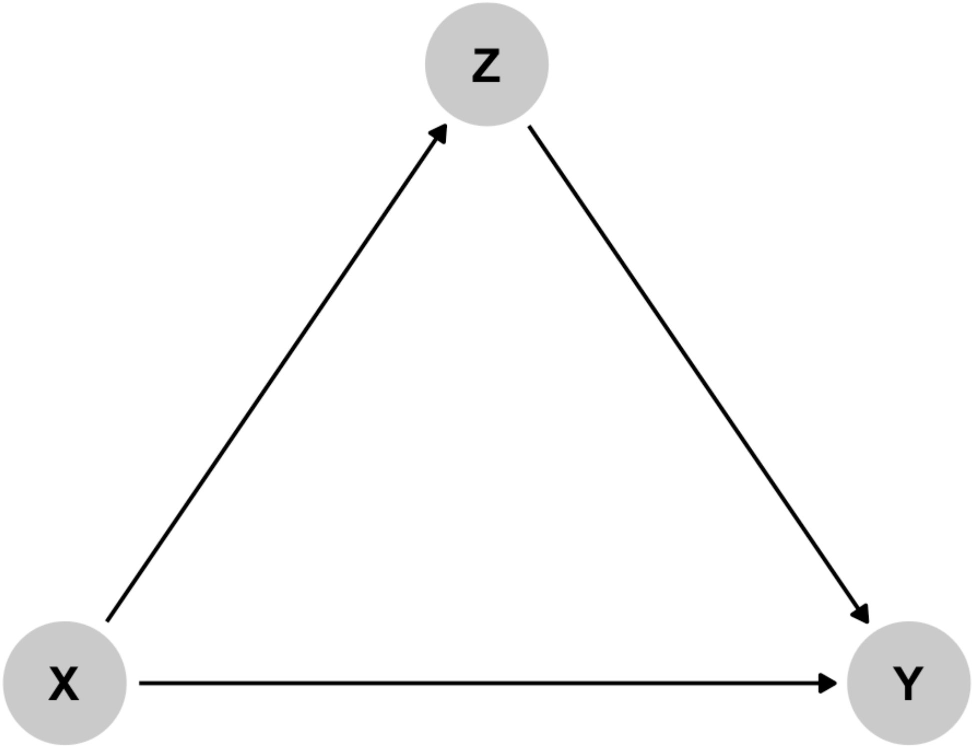
(Inverted fork)



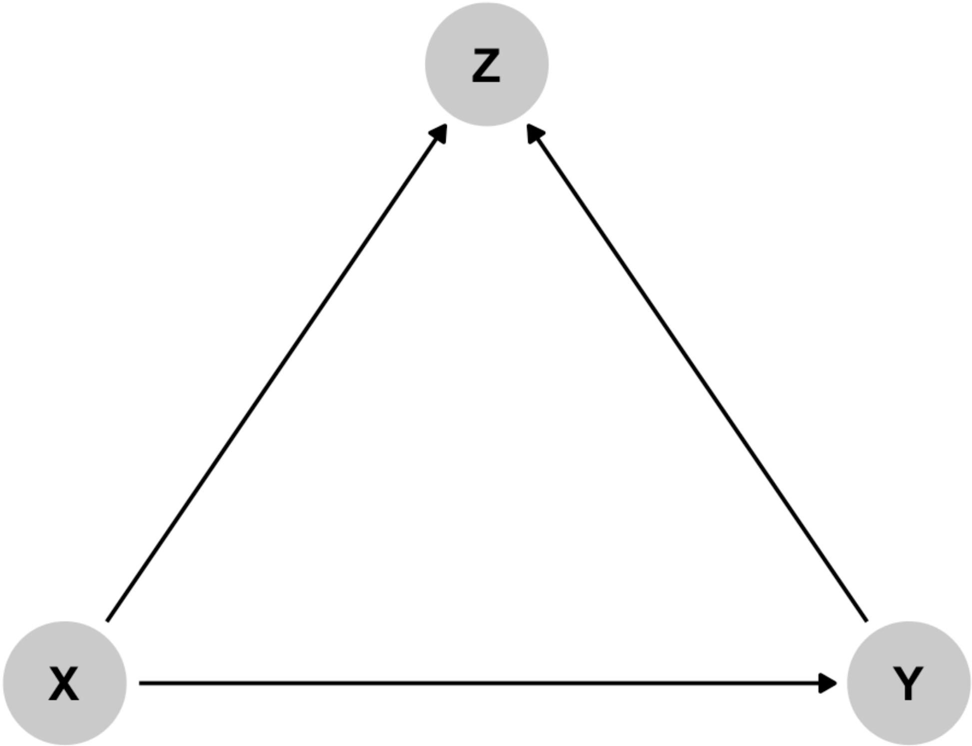

LUTRON


Z
X
Y

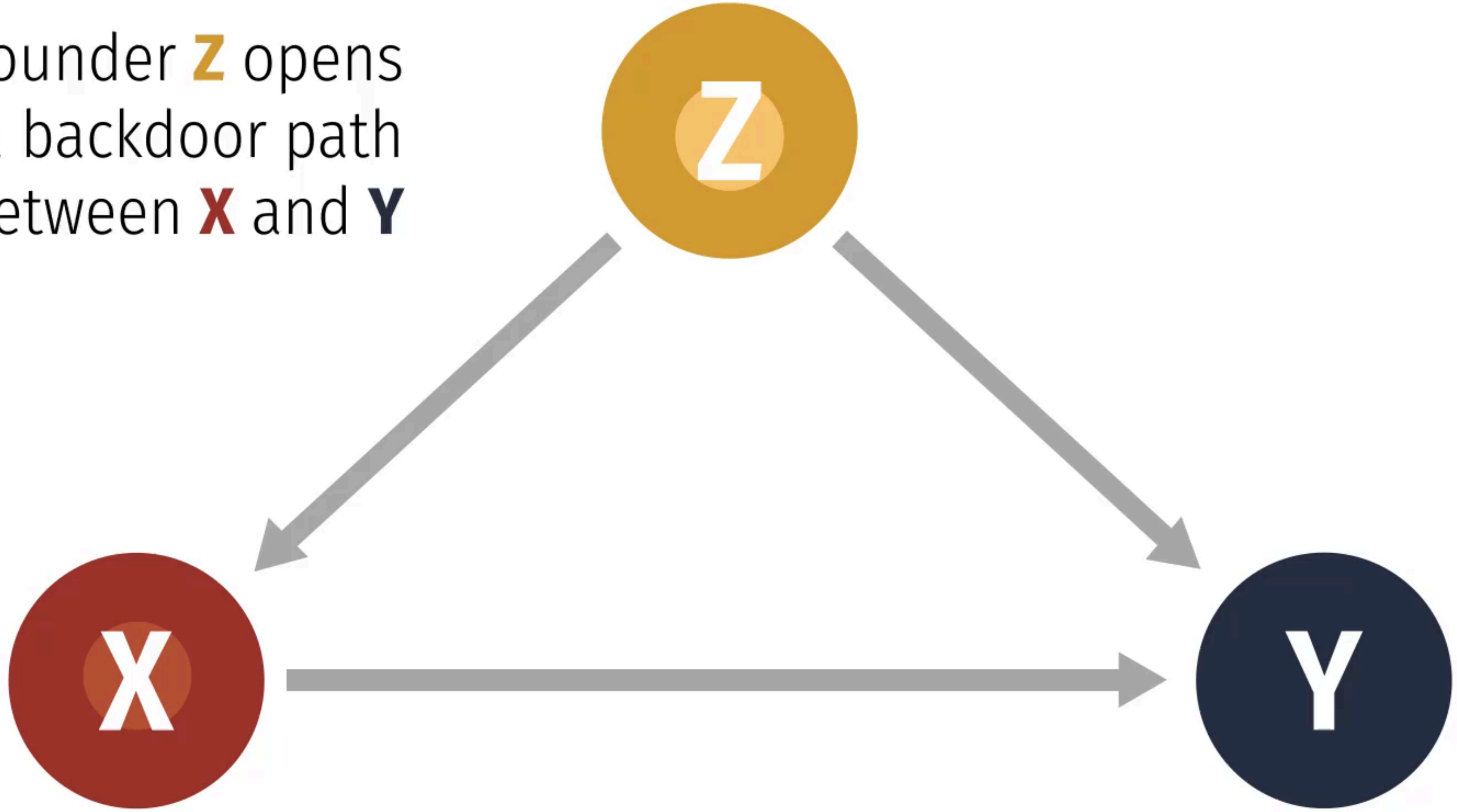

LUTRON


Z
X
Y


LUTRON

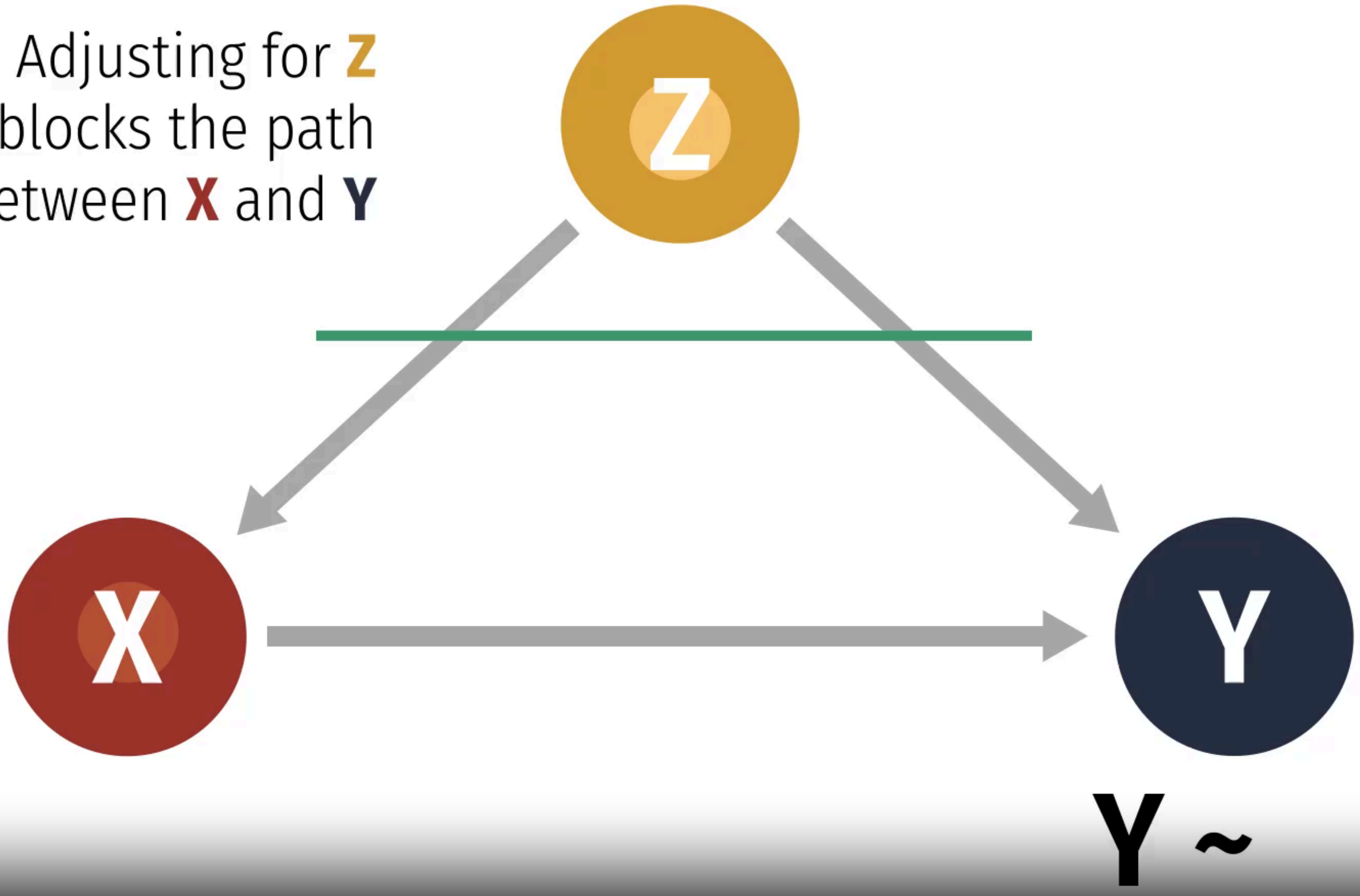

Z
X
Y

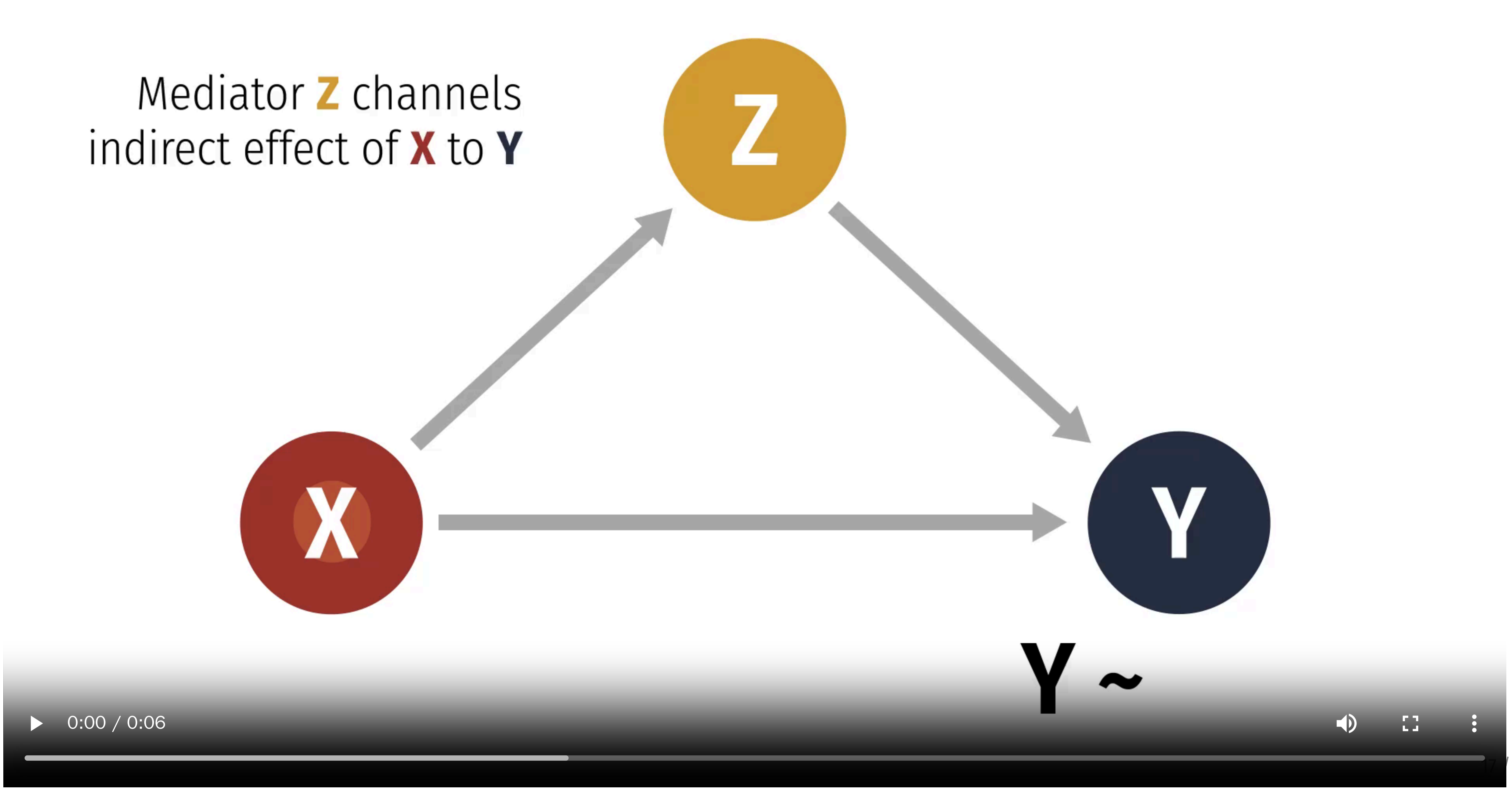
Confounder **Z** opens a backdoor path between **X** and **Y**



Y ~

Adjusting for Z blocks the path between X and Y




Mediator Z channels
indirect effect of X to Y
Z
X
Y
Y ~
0:00 / 0:06

d-separation

Except for the one arrow between X and Y,
no statistical association can flow between X and Y

This is **identification**—
all alternative stories are ruled out
and the relationship is isolated

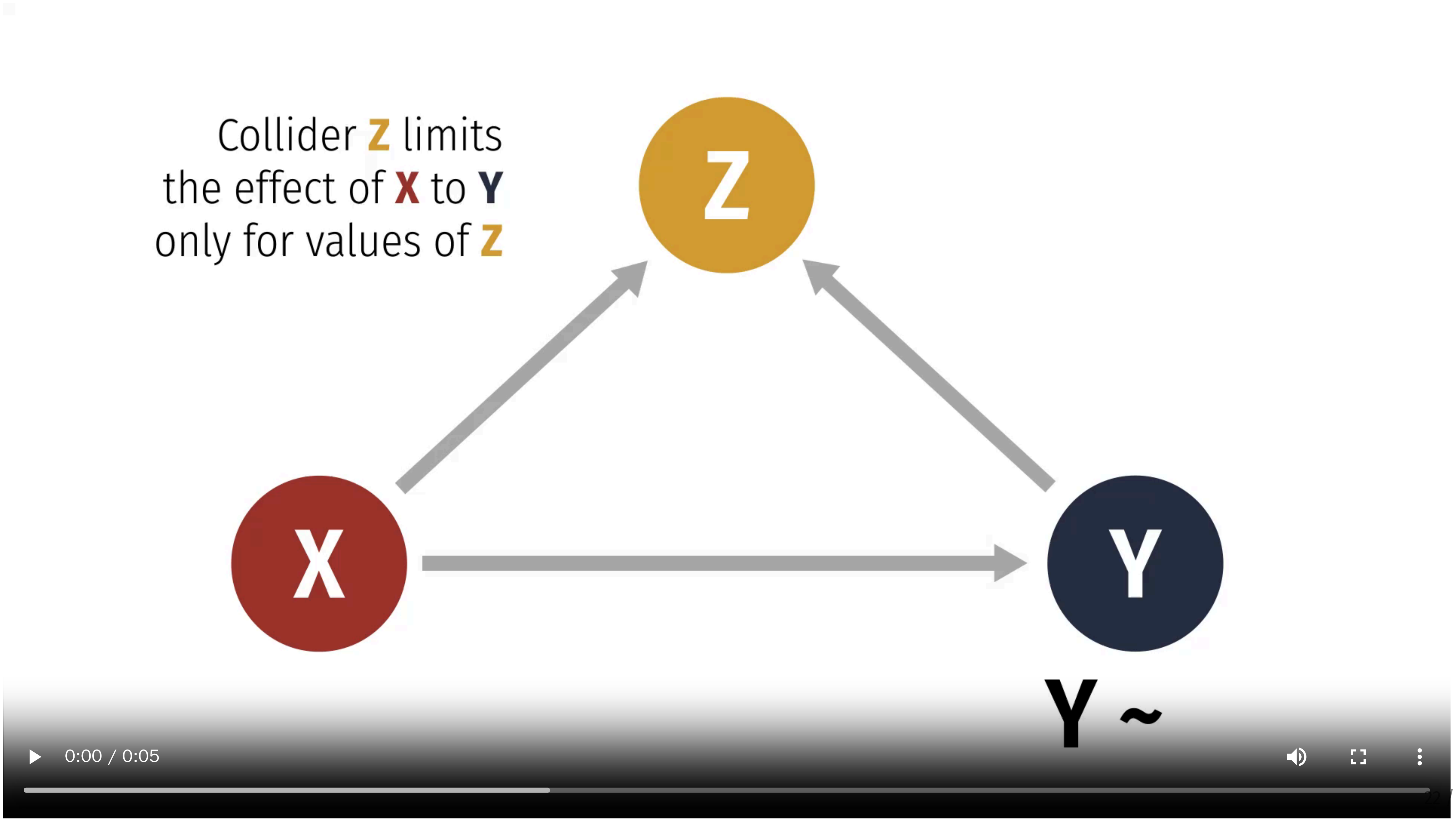
How exactly do we close backdoors?

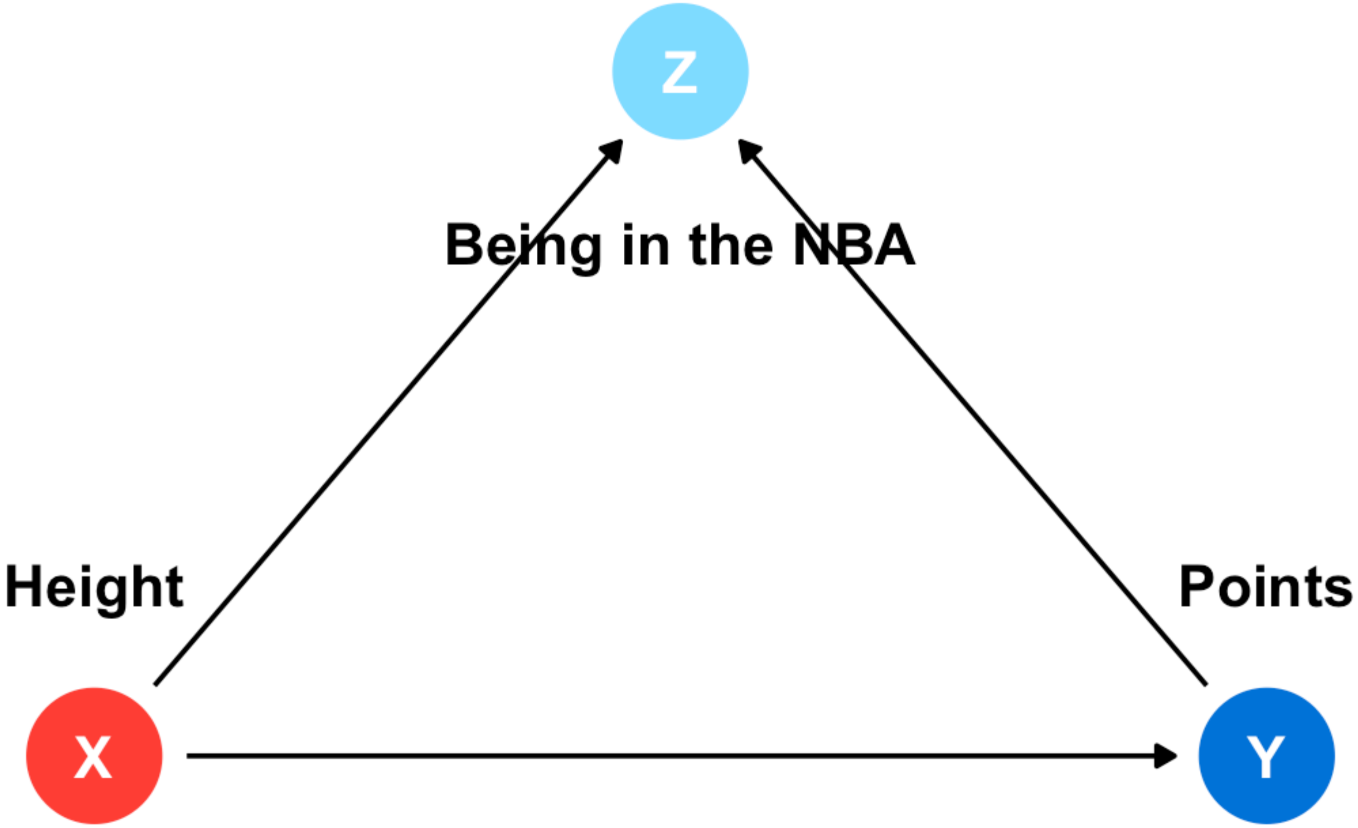
What about cycles?

Example time-based DAG

How exactly do colliders mess up your results?

It looks like you can still get the effect of X on Y


Collider Z limits
the effect of X to Y
only for values of Z
Z
X
Y
Y ~
0:00 / 0:05

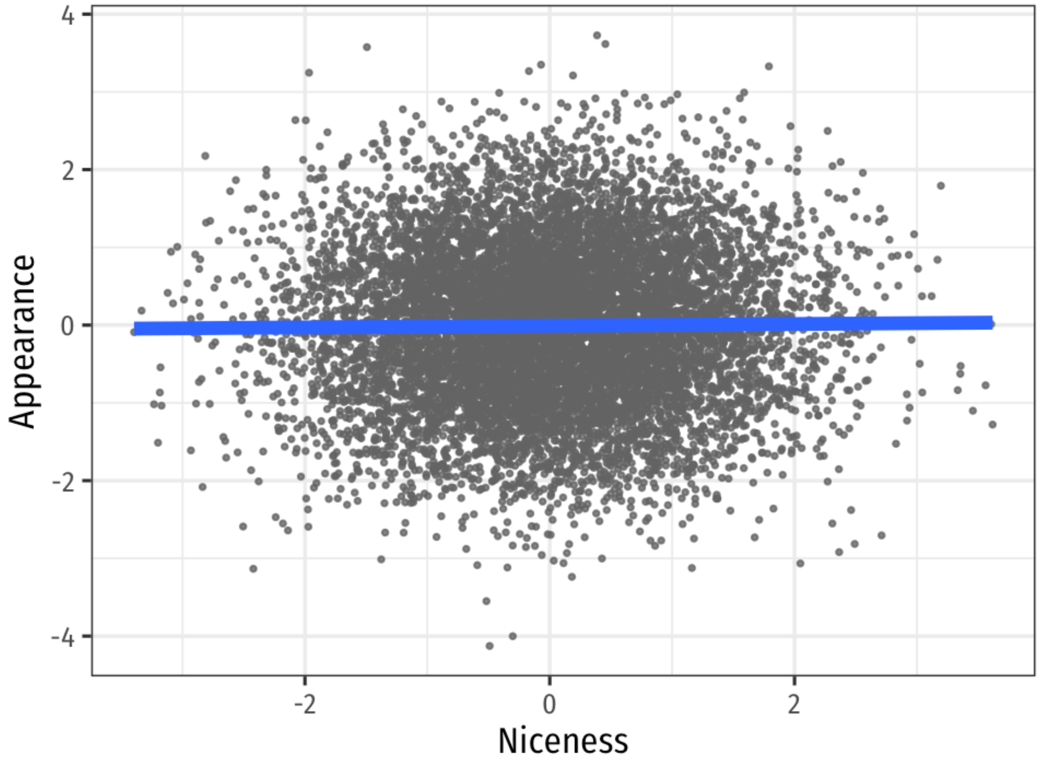

Z
Being in the NBA
Height
Points
X
Y

Sept. 10, 2021, 3:58 p.m. ET
By Davey Alba

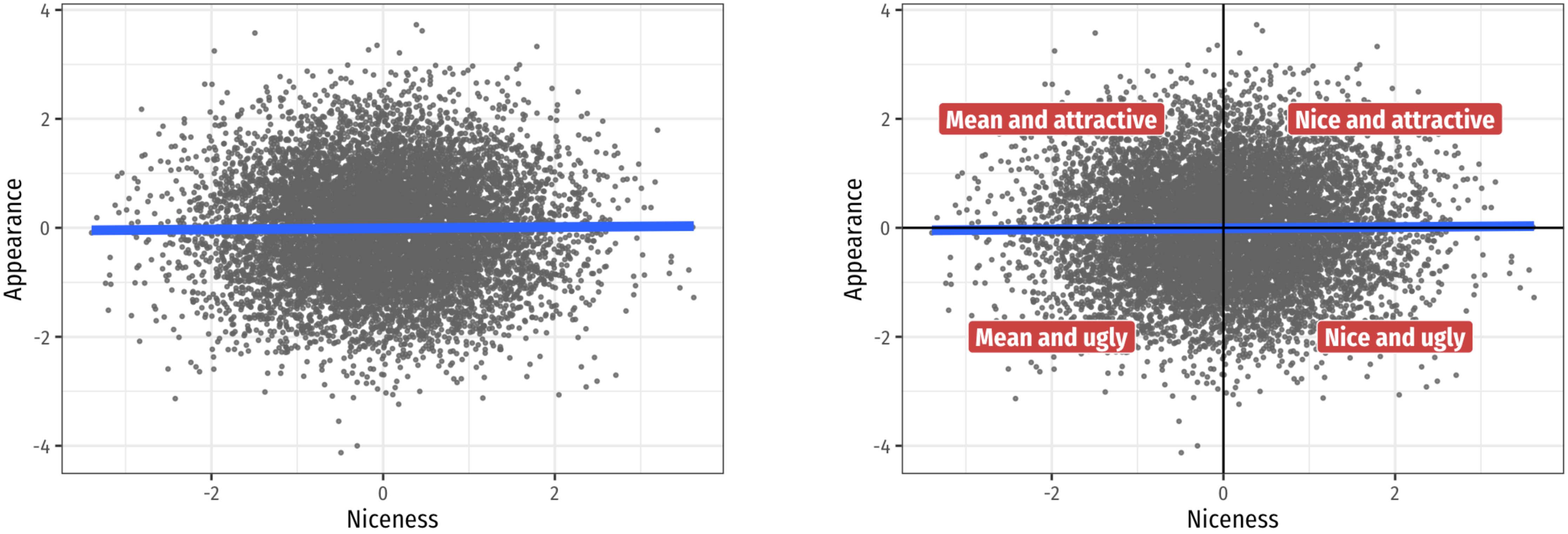
Facebook sent flawed data to misinformation researchers.

Mark Zuckerberg, chief executive of Facebook, testifying in Washington in 2018. Tom Brenner/The New York Times

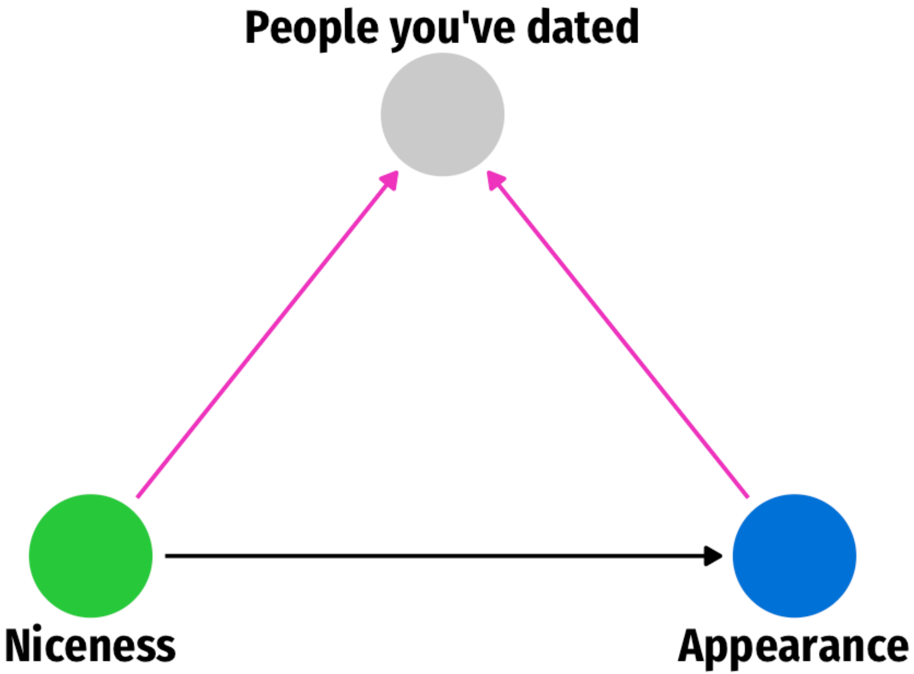
Does niceness improve appearance?



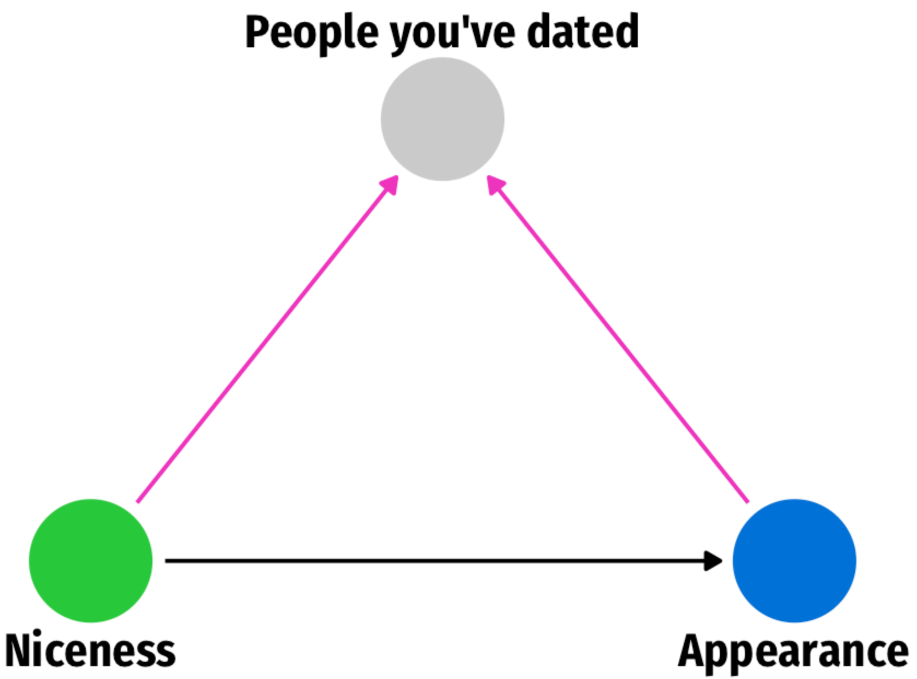
Does niceness improve appearance?

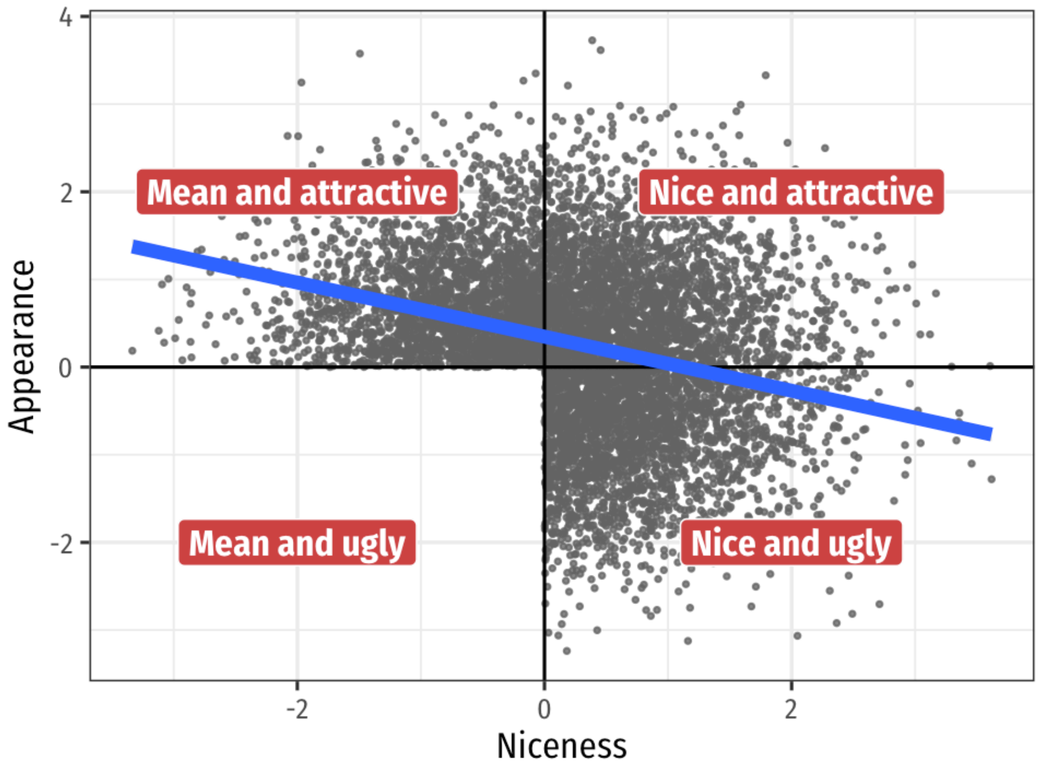


Collider distorts the true effect!

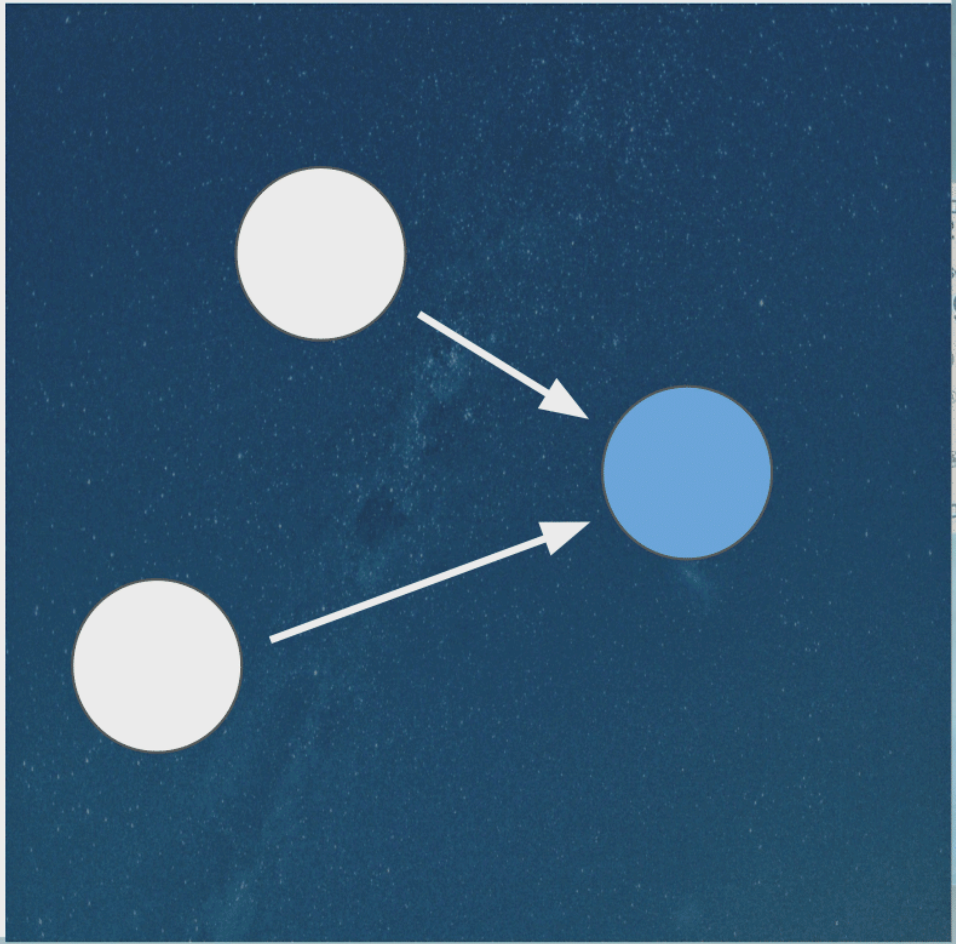


Collider distorts the true effect!



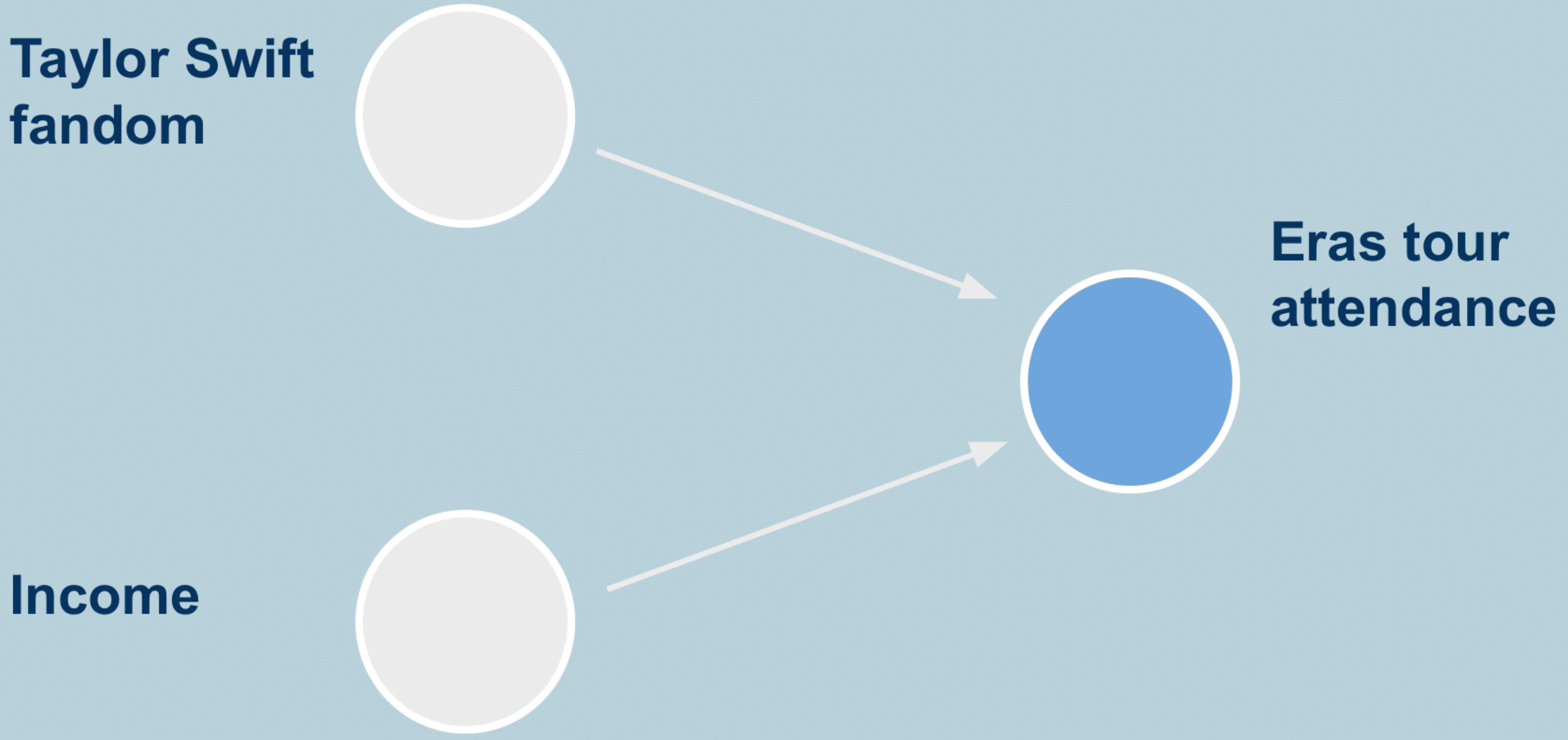


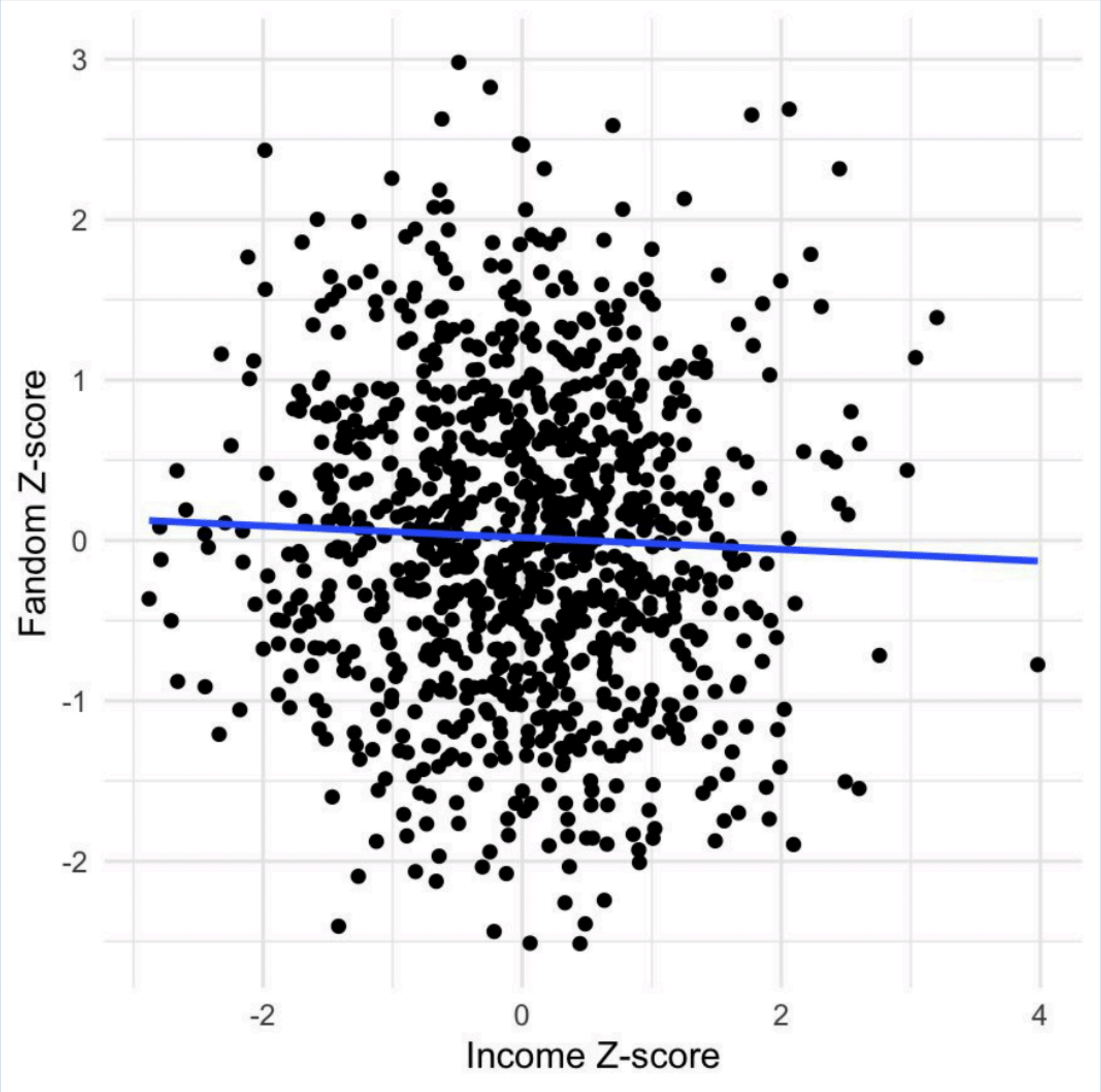
Colliders



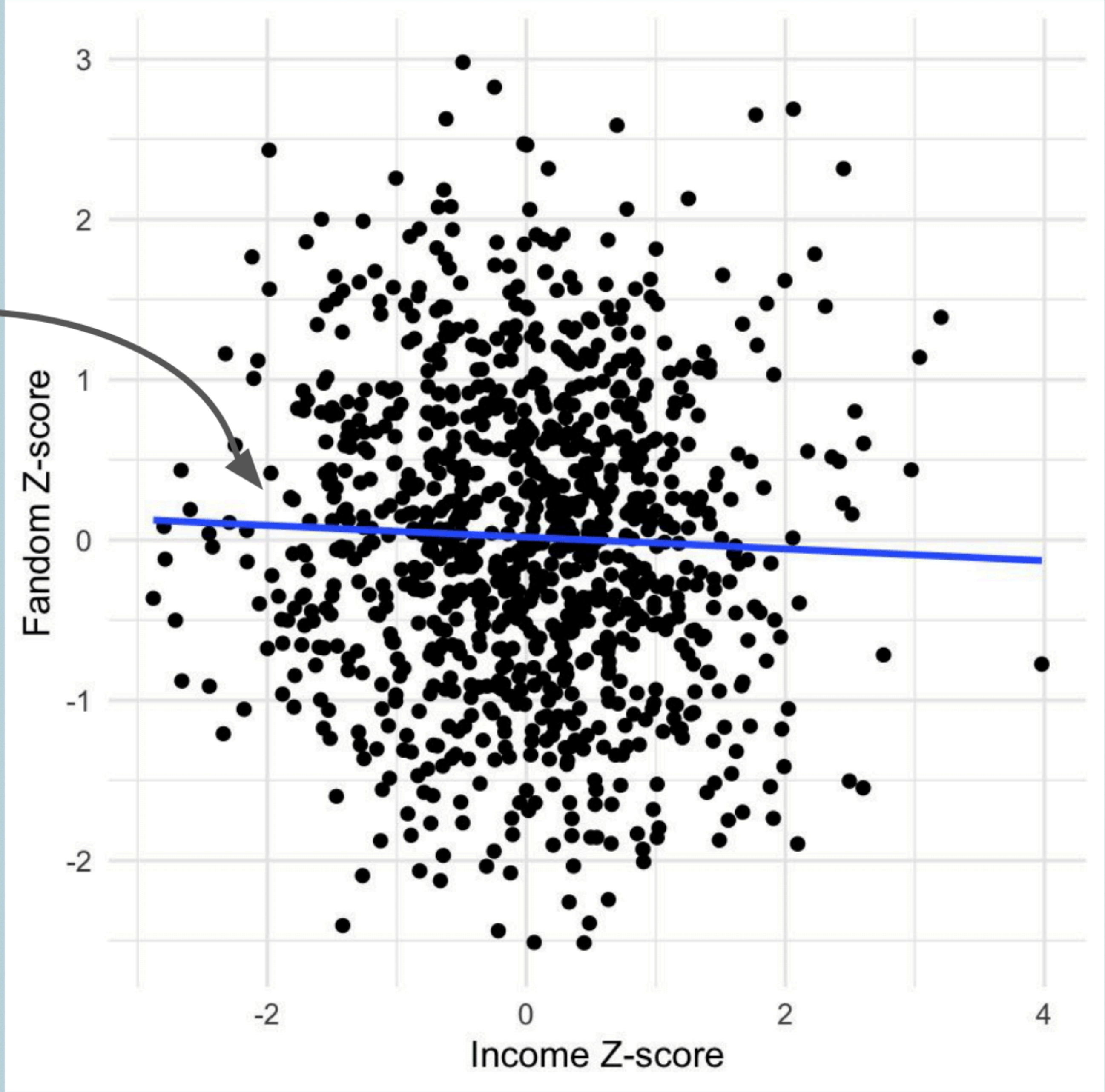
It's ME hi I'm the collider it's ME

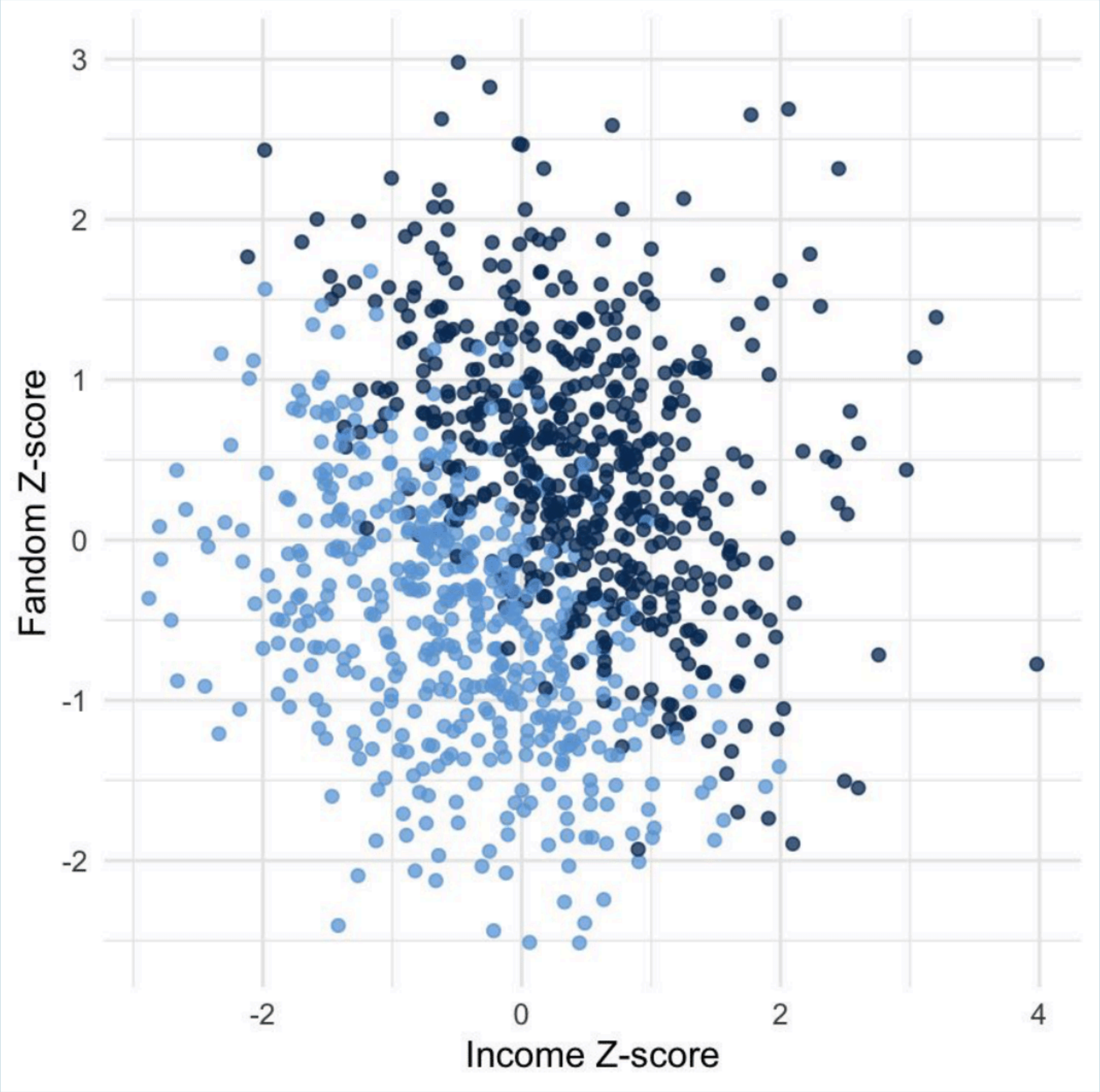
Lucy D'Agostino McGowan
Wake Forest University


Taylor Swift fandom
Income
Eras tour attendance

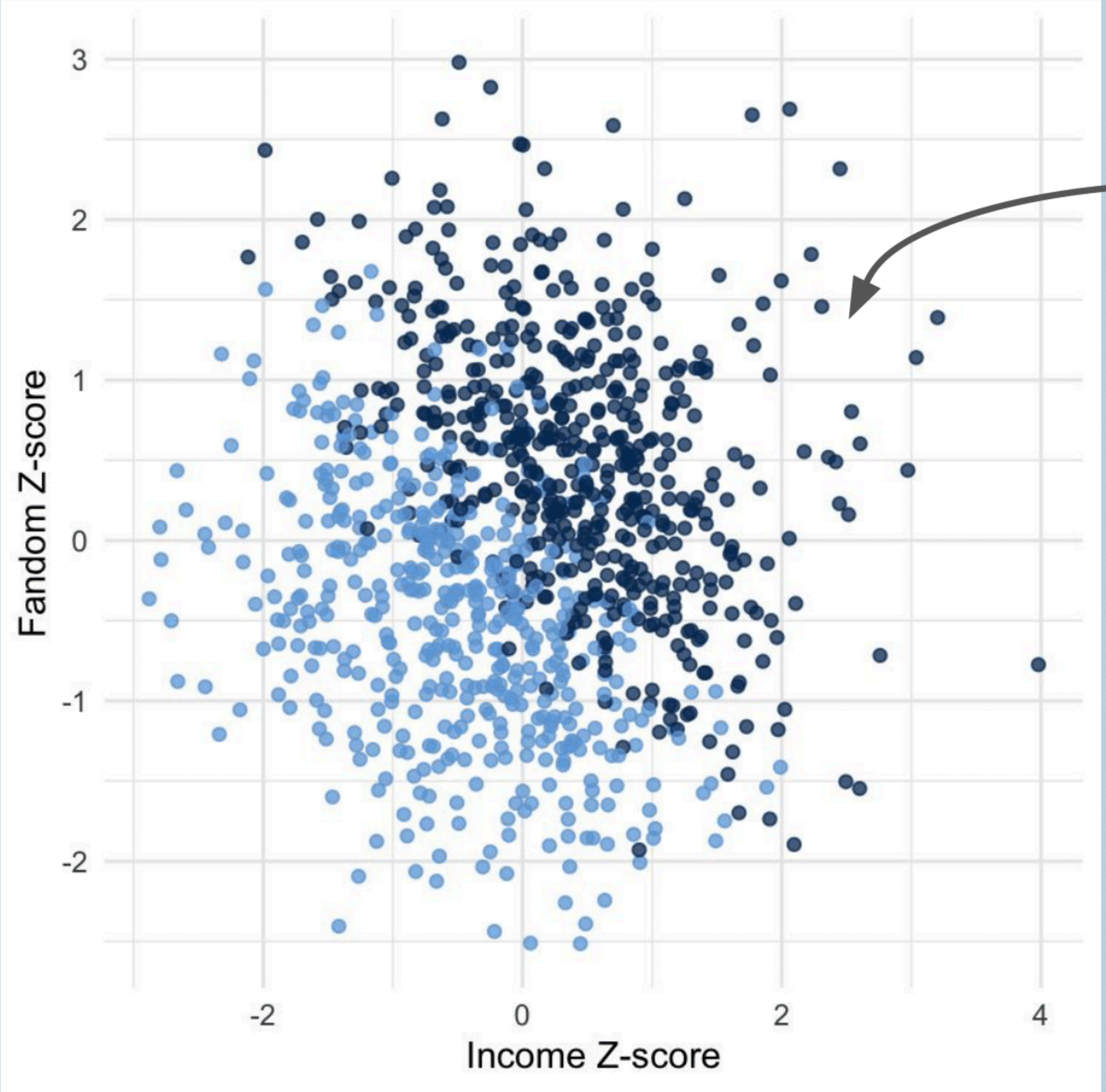

3
2
1
0
-1
-2
Fandom Z-score
-2
0
2
4
Income Z-score

No relationship between income and Taylor Swift fandom

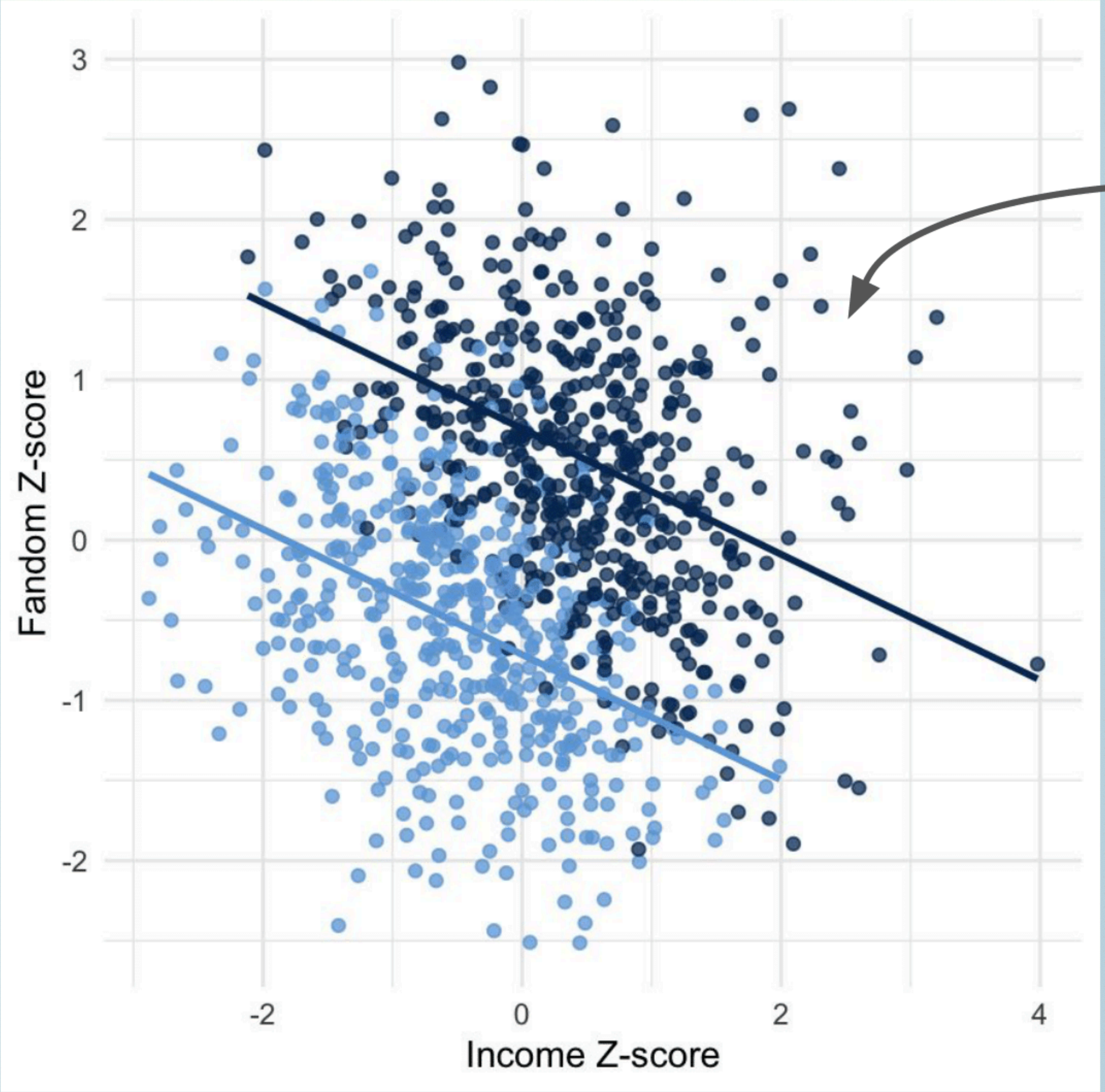




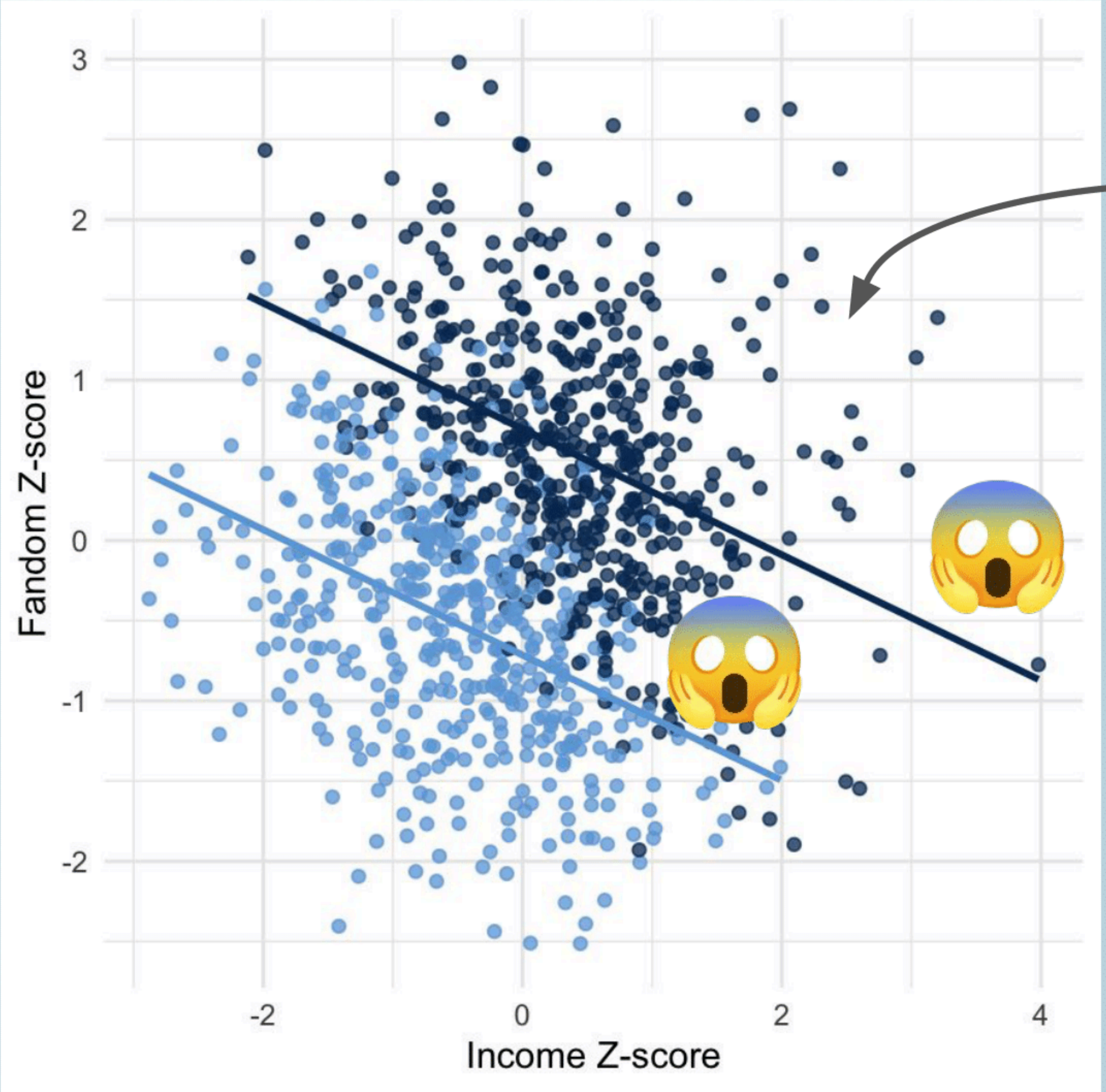
Fandom Z-score
Income Z-score
3
2
1
0
-1
-2
-2
0
2
4



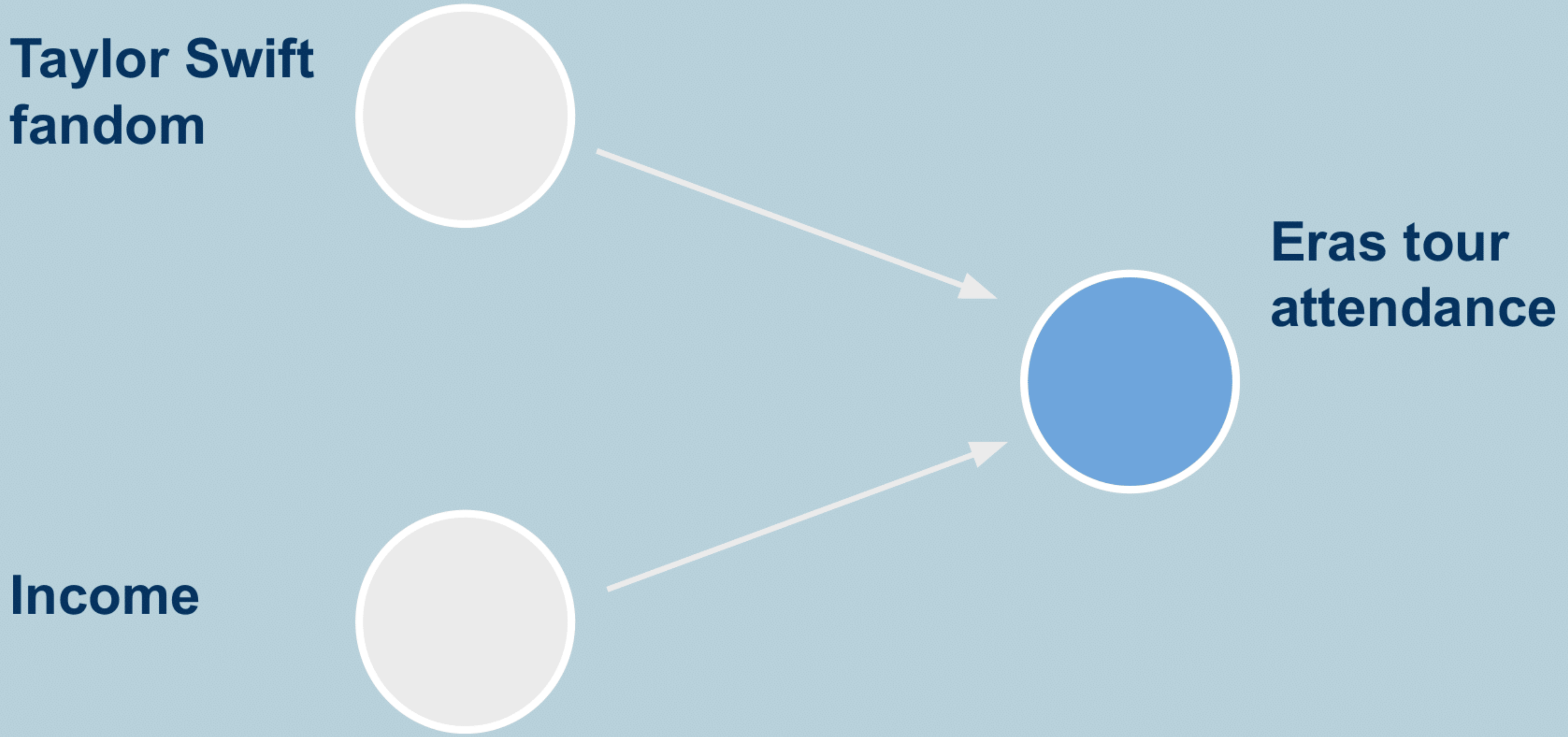
Attended Era's tour

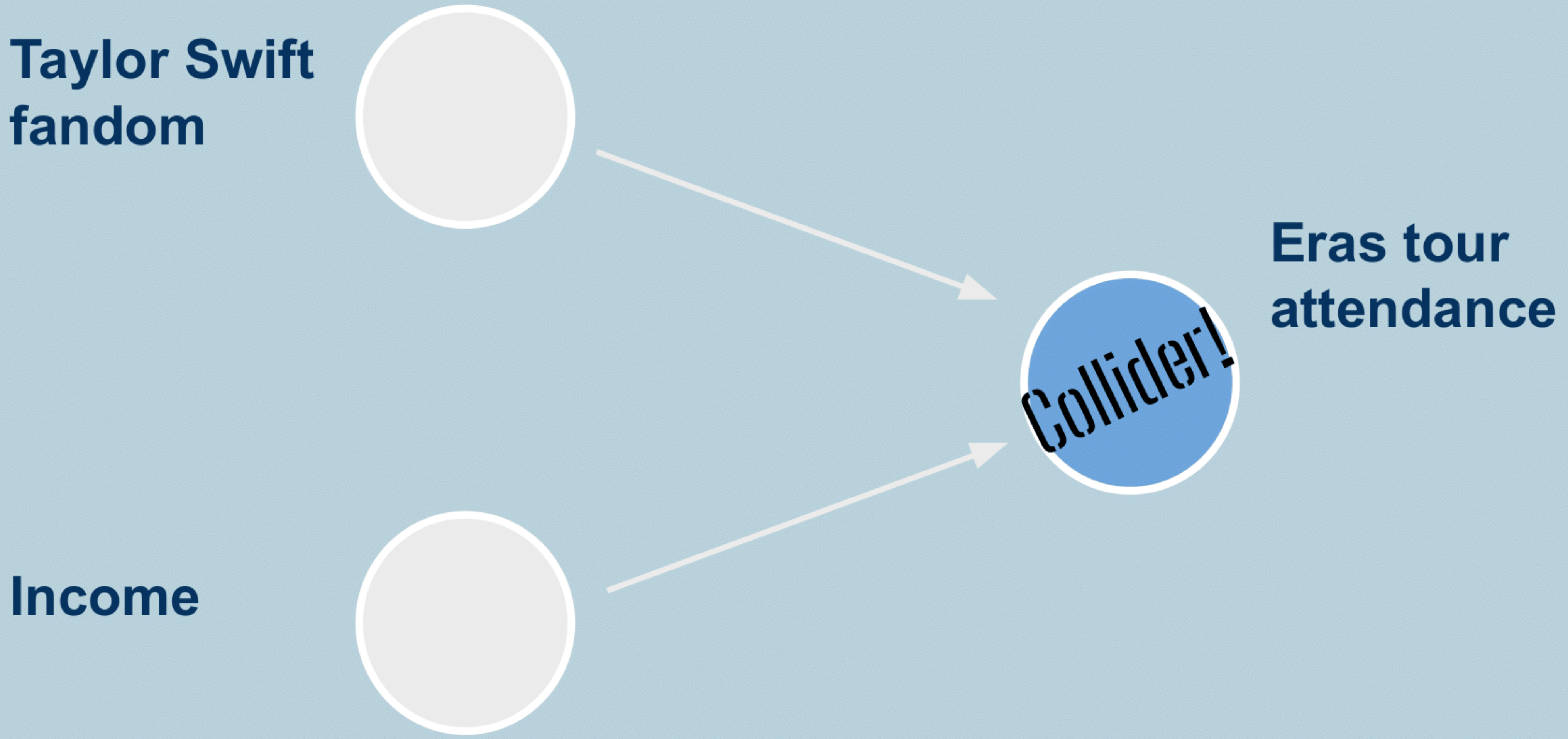


Attended Era's tour



Attended Era's tour


Taylor Swift
fandom
Income
Eras tour
attendance


Taylor Swift fandom
Income
Eras tour attendance
Collider!

What we want:

$$\widehat{\text{fandom}} = \widehat{\beta}_0 + \boxed{\widehat{\beta}_1}\,\text{income}$$

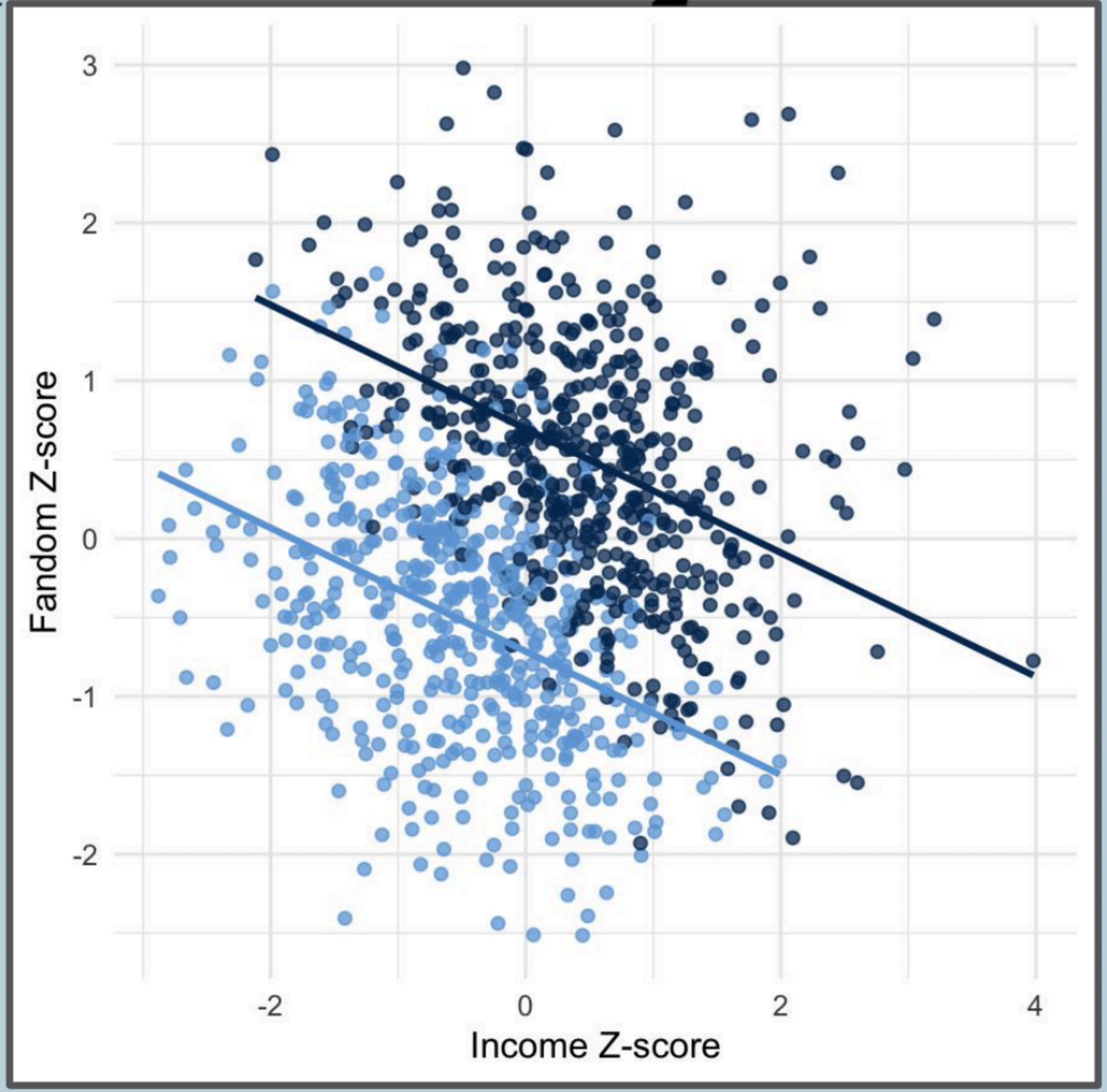
What we want:

$$\widehat{\text{fandom}} = \widehat{\beta}_0 + \widehat{\beta}_1 \text{income}$$

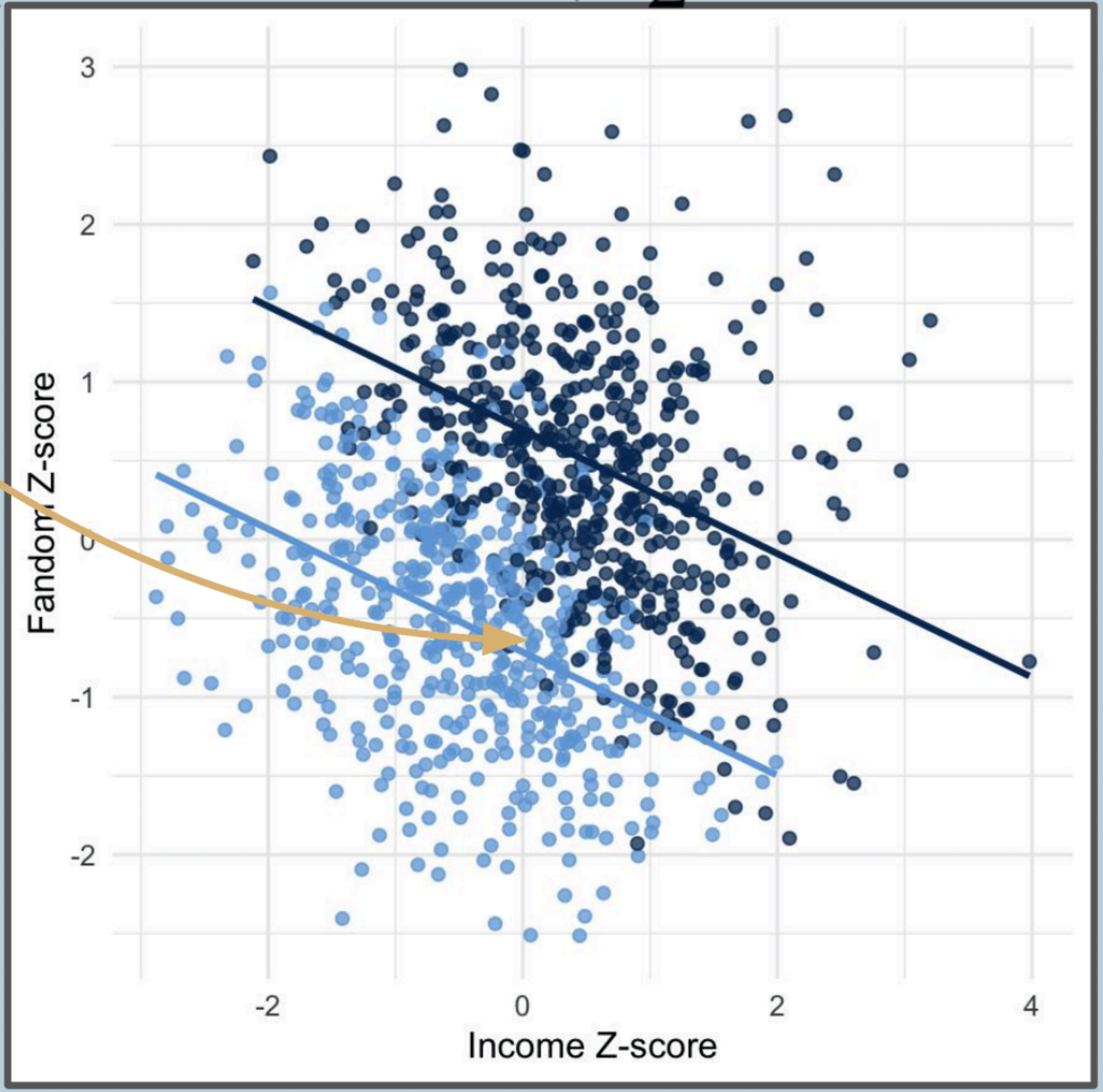
What we have:

$$\widehat{\text{fandom}} = \widehat{\beta}_0^* + \widehat{\beta}_1^* \text{income} + \widehat{\beta}_2^* \text{eras tour}$$

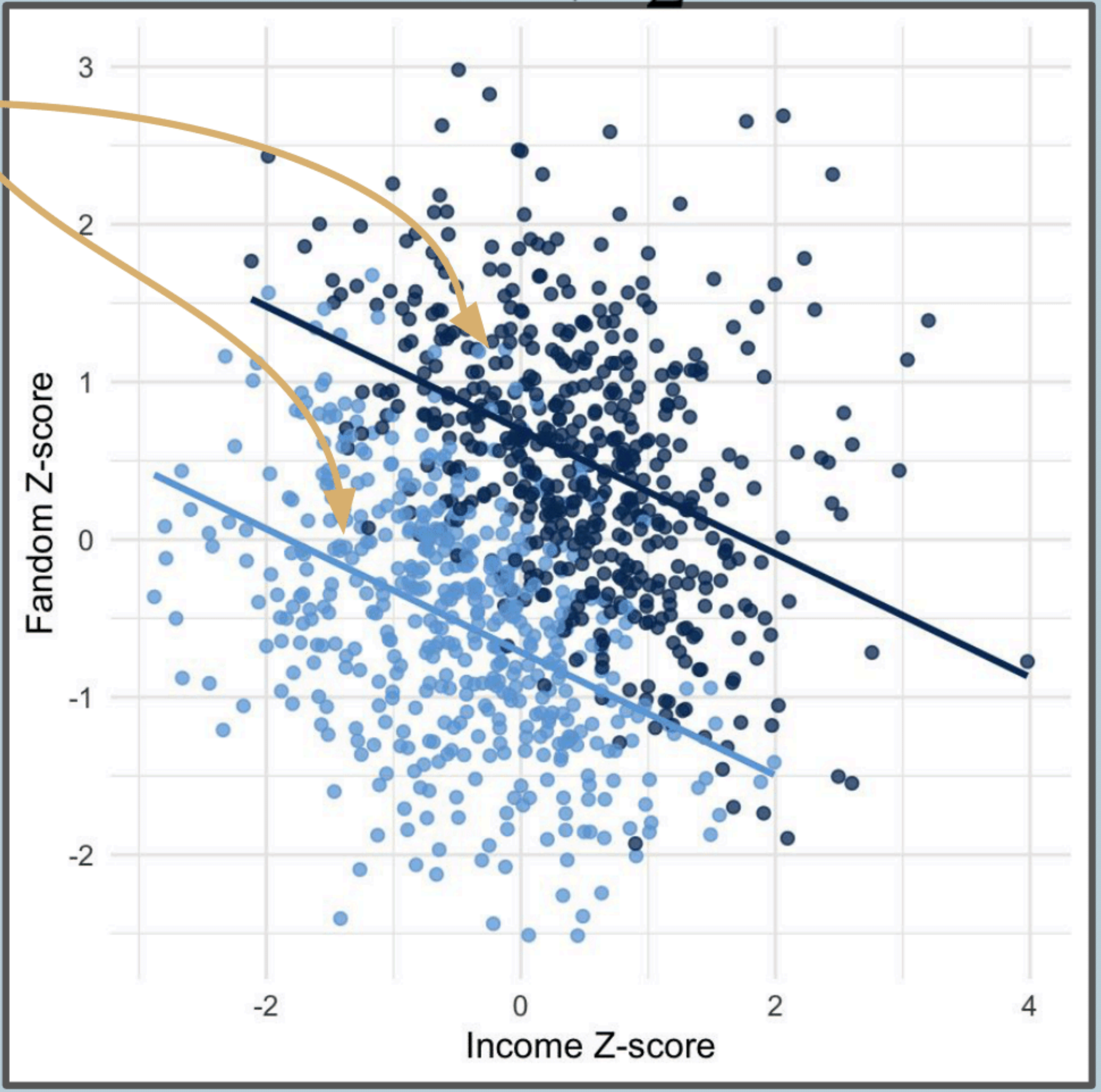
$$\widehat{\text{fandom}} = \widehat{\beta}_0^* + \widehat{\beta}_1^* \text{income} + \widehat{\beta}_2^* \text{eras tour}$$



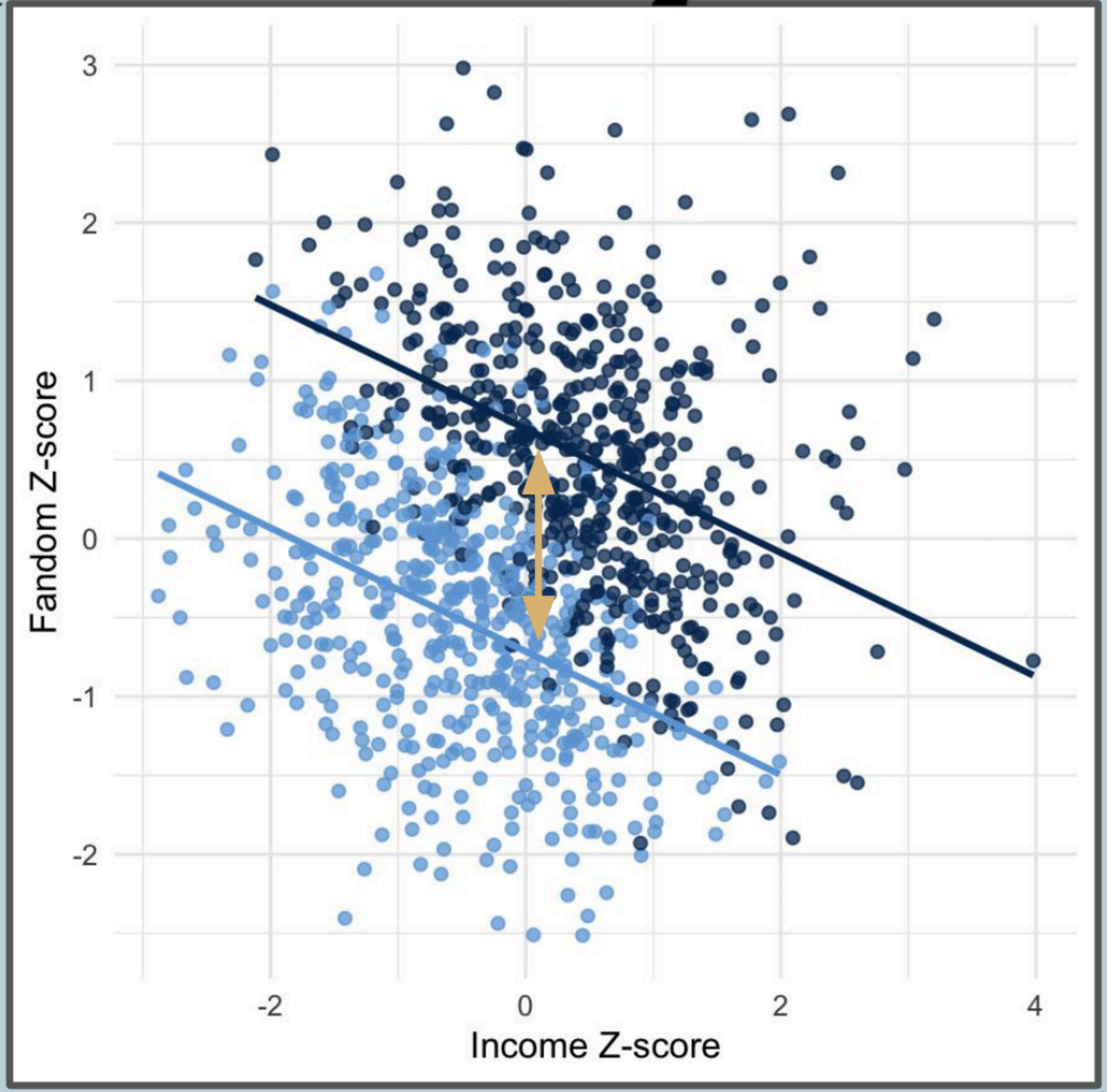
$$\widehat{\text{fandom}} = \boxed{\widehat{\beta}_0^*} + \widehat{\beta}_1^* \text{income} + \widehat{\beta}_2^* \text{eras tour}$$



$$\widehat{\text{fandom}} = \widehat{\beta}_0^* + \widehat{\beta}_1^* \text{income} + \widehat{\beta}_2^* \text{eras tour}$$

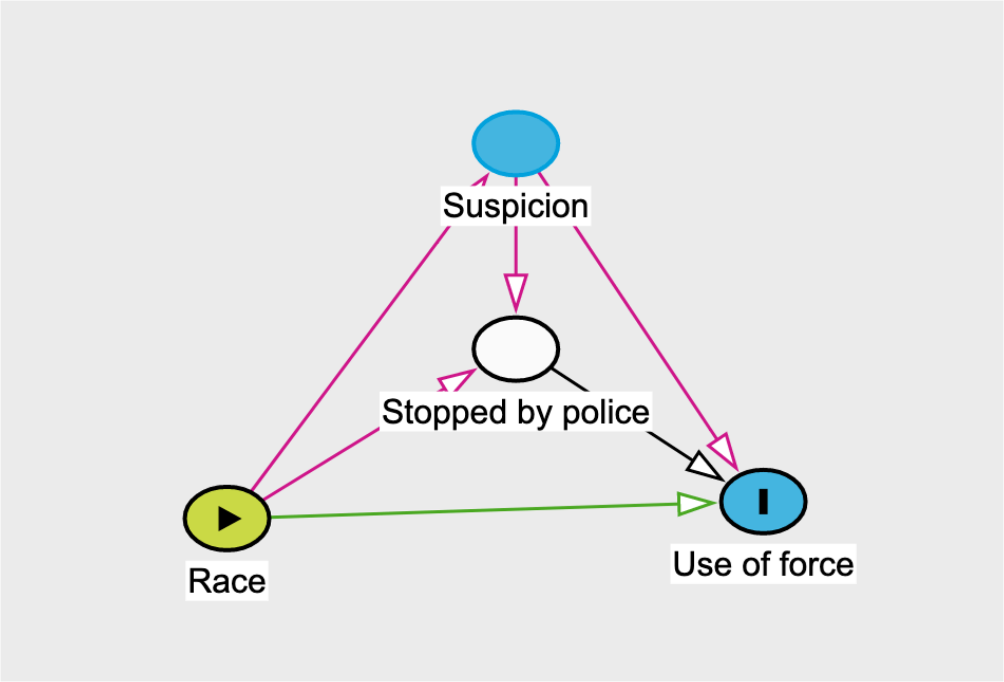


$$\widehat{\text{fandom}} = \widehat{\beta}_0^* + \widehat{\beta}_1^* \text{income} + \boxed{\widehat{\beta}_2^*} \text{eras tour}$$



Effect of race on police use of force using administrative data

Effect of race on police use of force using administrative data



American Political Science Review, Page 1 of 19
doi:10.1017/S0003055420000039

Administrative Records Mask Racially Biased Policing

DEAN KNOX *Princeton University*
WILL LOWE *Hertie School of Governance*
JONATHAN MUMMOLO *Princeton University*

Researchers often lack the necessary data to credibly estimate racial discrimination in policing. In particular, police administrative records lack information on civilians police observe but do not investigate. In this article, we show that if police racially discriminate when choosing whom to investigate, analyses using administrative records to estimate racial discrimination in police behavior are statistically biased, and many quantities of interest are unidentified—even among investigated individuals—absent strong and untestable assumptions. Using principal stratification in a causal mediation framework, we derive the exact form of the statistical bias that results from traditional estimation. We develop a bias-correction procedure and nonparametric sharp bounds for race effects, replicate published findings, and show the traditional estimator can severely underestimate levels of racially biased policing or mask discrimination entirely. We conclude by outlining a general and feasible design for future studies that is robust to this inferential snare.

Concern over racial bias in policing, and the public availability of large administrative data sets documenting police–civilian interactions, have prompted a raft of studies attempting to quantify the effect of civilian race on law enforcement behavior. These studies consider a range of outcomes including ticketing, stop duration, searches, and the use of force (e.g., Antonovics and Knight 2009; Fryer 2019; Ridgeway 2006; Nix et al. 2017). Most research in this area attempts to adjust for omitted variables that may correlate with suspect race and the outcome of interest. In contrast, this study addresses a more fundamental problem that remains even if the vexing issue of omitted variable bias is solved: the inevitable statistical bias that results from studying racial discrimination using records that are themselves the product of racial discrimination (Angrist and Pischke 2008; Elwert and Winship 2014; Rosenbaum 1984). We show that when there is any biased absent additional data and/or strong and untestable assumptions.

This study makes several contributions. We clarify the causal estimands of interest in the study of racially discriminatory policing—quantities that many studies appear to be targeting, but are rarely made explicit—and show that the conventional approach fails to recover any known causal quantity in reasonable settings. Next, we highlight implicit and highly implausible assumptions in prior work and derive the statistical bias when they are violated. We proceed to develop informative nonparametric sharp bounds for the range of possible race effects, apply these in a reanalysis and extension of a prominent article on police use of force (Fryer 2019), and present bias-corrected results that suggest this and similar studies drastically underestimate the level of racial bias in police–civilian interactions. Finally, we outline strategies for future data collection and re-

Logic models, DAGs, and measurement

What's the difference between logic models and DAGs?

Can't I just remake my logic model in Dagitty and be done?

DAGs vs. Logic models

DAGs are a *statistical* tool

Describe a data-generating process and isolate/identify relationships

DAGs vs. Logic models

DAGs are a *statistical* tool

Describe a data-generating process and isolate/identify relationships

Logic models are a *managerial* tool

Oversee the inner workings of a program and its theory

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Potential outcomes vs. do() notation

Expectations

$$\text{E}(\cdot), \mathbf{E}(\cdot), \mathbb{E}(\cdot) \quad \text{vs.} \quad \text{P}(\cdot)$$

Basically a fancy way of saying "average"

Potential outcomes and CATEs example

Why can't we just subtract the averages between treated and untreated groups?

When you're making groups for CATE, how do you decide what groups to put people in?

Slides from lecture

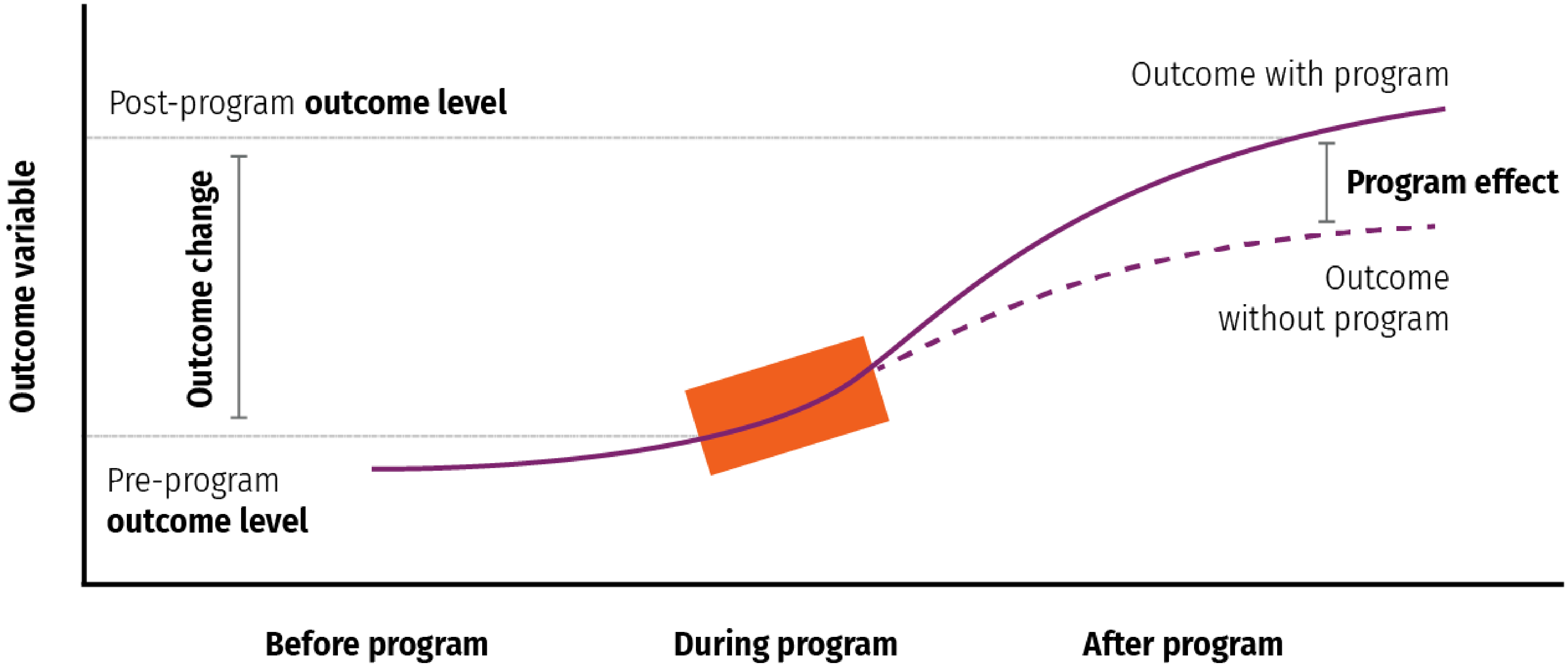
Unconfoundedness assumption

How can we assume/pretend that treatment was randomly assigned within each age?

It seems unlikely. Wouldn't there be other factors within the older/younger group that make a person more/less likely to engage in treatment (e.g., health status)?

Slides from lecture

Outcomes and programs



Causal effects with potential outcomes

Potential outcomes notation:

$$\delta \ = \tfrac{1}{n}\sum_{i=1}^{n} Y_i(1) - Y_i(0)$$

or alternatively with $\mathbf{E}$

$$\delta \ = \mathbf{E}[Y_i(1) - Y_i(0)]$$

Causal effects with do()

Pearl notation:

$$\delta = \mathbf{E}[Y_i \mid \text{do}(X = 1) - Y_i \mid \text{do}(X = 0)]$$

or more simply

$$\delta = \mathbf{E}[Y_i \mid \text{do}(X)]$$

$$\mathbf{E}[Y_i \mid \mathrm{do}(X)]$$

$$=$$

$$\mathbf{E}[Y_i(1) - Y_i(0)]$$

We can't see this

$$\mathbf{E}[Y_i \mid \text{do}(X)] \quad \text{or} \quad \mathbf{E}[Y_i(1) - Y_i(0)]$$

So we find the average causal effect (ACE)

$$\hat{\delta} = \mathbf{E}[Y_i \mid X = 1] - \mathbf{E}[Y_i \mid X = 0]$$

$$\overbrace{\mathbf{E}(y \mid \mathrm{do}(x))}^{\text{The average population-level change in } y \text{ when } \textit{directly intervening} \text{ (or doing) } x} \quad \neq \quad \overbrace{\mathbf{E}(y \mid x)}^{\text{The average population-level change in } y \text{ when accounting for } \textit{observed } x}$$

$$\underbrace{\mathbf{E}(y \mid \mathrm{do}(x))}_{\text{Causation}} \quad \neq \quad \underbrace{\mathbf{E}(y \mid x)}_{\text{Correlation}}$$

do-calculus and adjustment

DAGs and identification

DAGs and identification

DAGs are a statistical tool, but they don't tell you what statistical method to use

DAGs and identification

DAGs are a statistical tool, but they don't tell you what statistical method to use

DAGs help you with the **identification strategy**

Thomas Massie
@RepThomasMassie

Over 70% of Americans who died with COVID, died on Medicare, and some people want #MedicareForAll ?

11:00 AM · Feb 9, 2022 · Twitter for iPhone

Easist identification

Identification through research design

RCTs

When treatment is randomized, delete all arrows going into it

No need for any do-calculus!

Most other identification

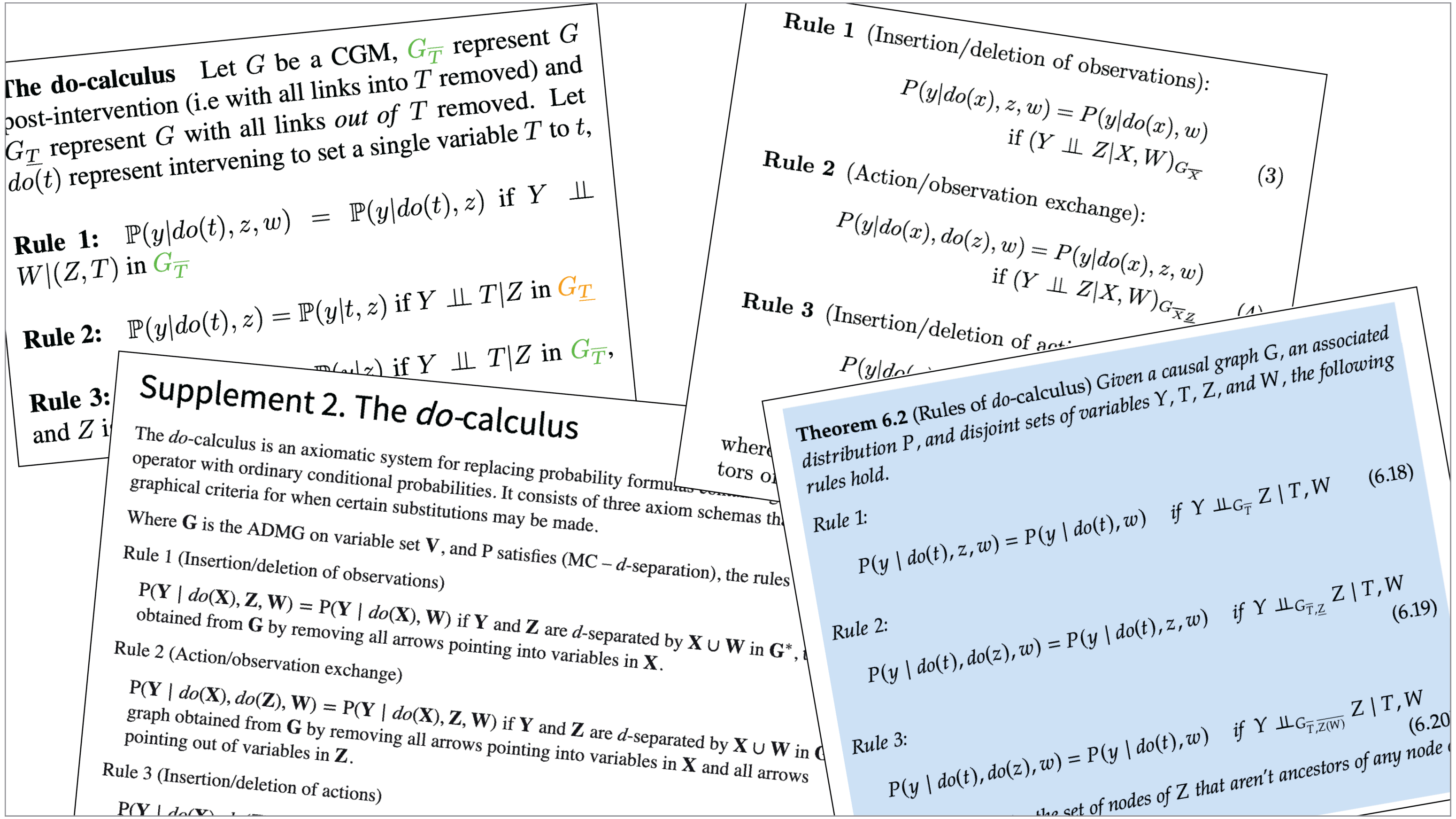
Identification through do-calculus

Rules for graph surgery

Backdoor adjustment and frontdoor adjustment are special common patterns of do-calculus

Where can we learn more about *do*-calculus?

Here!



Rule 1: Decide if we can ignore an observation

$$P(y \mid z, \mathrm{do}(x), w) = P(y \mid \mathrm{do}(x), w) \qquad \text{if } (Y \perp Z \mid W, X)_{G_{\overline{X}}}$$

Rule 2: Decide if we can treat an intervention as an observation

$$P(y \mid \mathrm{do}(z), \mathrm{do}(x), w) = P(y \mid z, \mathrm{do}(x), w) \qquad \text{if } (Y \perp Z \mid W, X)_{G_{\overline{X}, \underline{Z}}}$$

Rule 3: Decide if we can ignore an intervention

$$P(y \mid \mathrm{do}(z), \mathrm{do}(x), w) = P(y \mid \mathrm{do}(x), w) \qquad \text{if } (Y \perp Z \mid W, X)_{G_{\overline{X}, \overline{Z(W)}}}$$

$$
\begin{aligned}
P(y \mid \operatorname{do}(x)) &= \sum_z P(y \mid \operatorname{do}(x), z) \times P(z \mid \operatorname{do}(x)) && \text{[Marginalization across } z + \text{chain rule for conditional probabilities]} \\
&= \sum_z P(y \mid x, z) \times P(z \mid \operatorname{do}(x)) && \text{[Use Rule 2 to treat } \operatorname{do}(x) \text{ as } x\text{]} \\
&= \sum_z P(y \mid x, z) \times P(z \mid \text{nothing!}) && \text{[Use Rule 3 to nuke } \operatorname{do}(x)\text{]} \\
&= \sum_z P(y \mid x, z) \times P(z) && \text{[Final backdoor adjustment formula!]}
\end{aligned}
$$

Adjusting for backdoor confounding

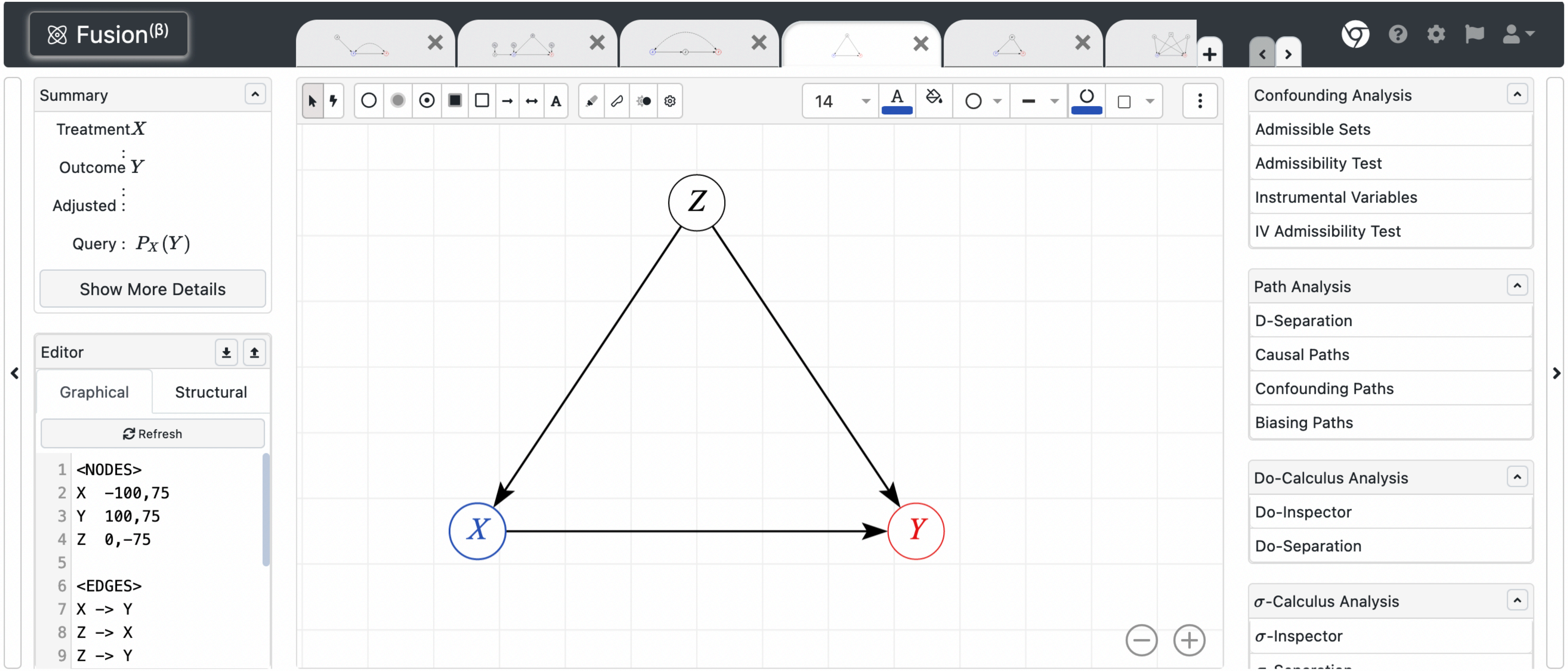
$$\underbrace{\mathbf{E}(y \mid \mathrm{do}(x))}_{\text{Causal effect of } x \text{ on } y} = \underbrace{\sum_z}_{\text{Sum across all values of } z} \underbrace{\mathbf{E}(y \mid x, z)}_{\text{Conditional mean of } y, \text{ given } x \text{ and } z\ldots} \times \underbrace{\mathbf{P}(z)}_{\ldots \text{ weighted by } z}$$

Adjusting for frontdoor confounding

More complex DAGs without obvious backdoor or frontdoor solutions

Chug through the rules of do-calculus to see if the relationship is identifiable

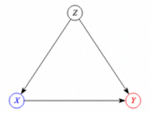
Causal Fusion



Fusion(β)
Summary
Treatment : X
Outcome : Y
Adjusted :
Query : P_X(Y)
Show More Details
Editor
Graphical
Structural
Refresh
1 <NODES>
2 X -100,75
3 Y 100,75
4 Z 0,-75
5
6 <EDGES>
7 X -> Y
8 Z -> X
9 Z -> Y
14
A
Z
X
Y
Confounding Analysis
Admissible Sets
Admissibility Test
Instrumental Variables
IV Admissibility Test
Path Analysis
D-Separation
Causal Paths
Confounding Paths
Biasing Paths
Do-Calculus Analysis
Do-Inspector
Do-Separation
σ-Calculus Analysis
σ-Inspector

Compute | The causal effect of X on Y conditional on with do : (Query: $P_X(Y)$ | Non-Parametric | Clear

1 $$P_X(Y) = \sum_Z P(Y|X,Z)\,P(Z)$$



Load
Estimation
Derivation
Remove

Simplified Obtained by Back-Door adjustment with an admissible set $\{Z\}$

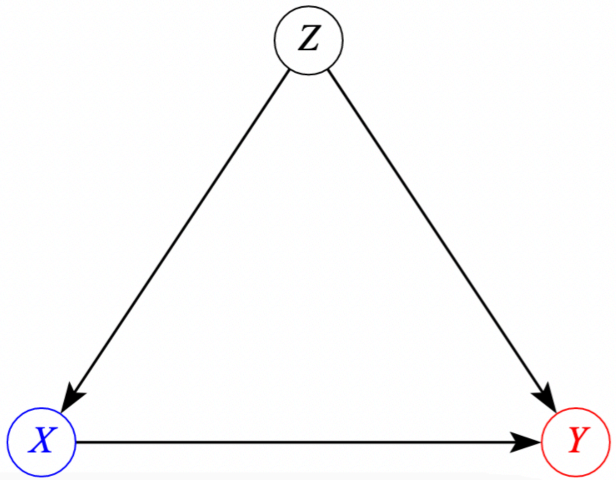
Do-Calculus

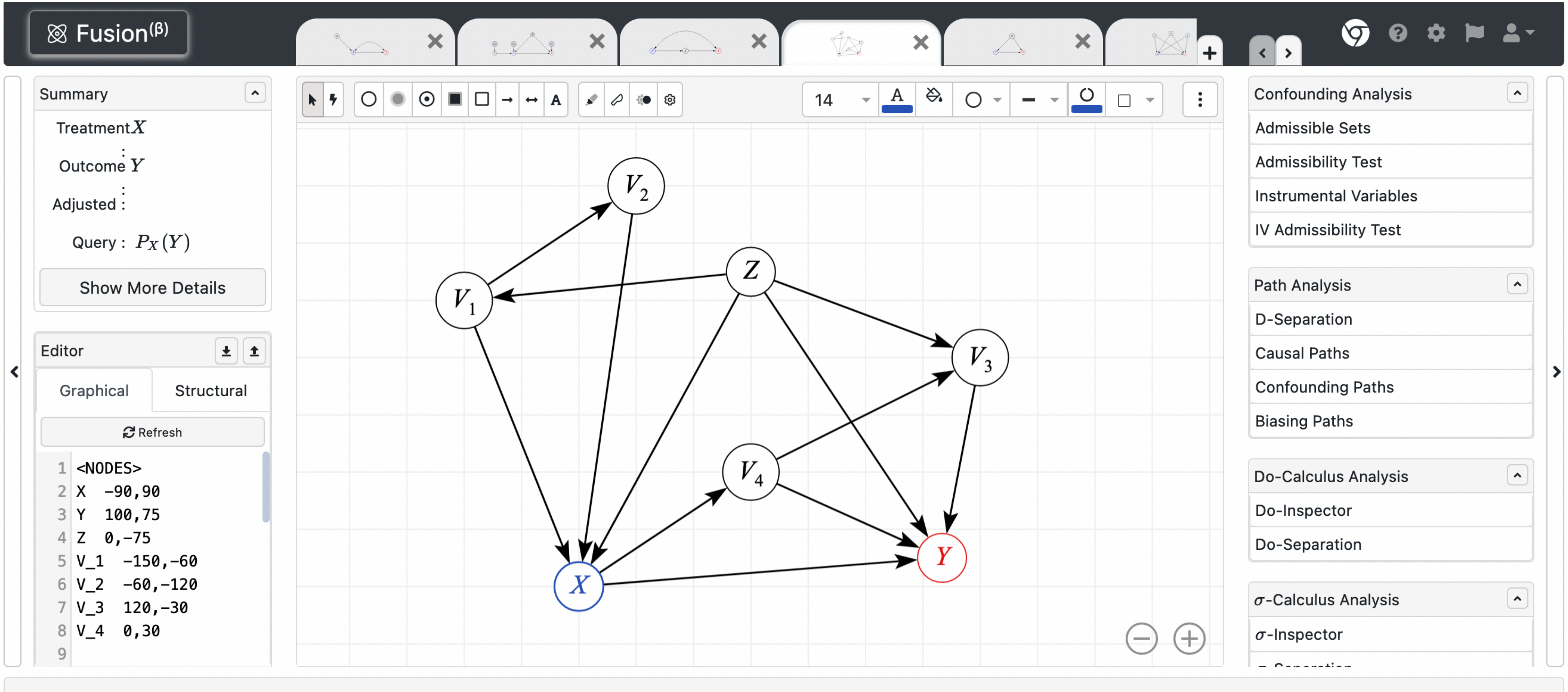
$P_X(Y)$		(1)
$\sum_Z P_X(Y\|Z)\,P_X(Z)$	Summing over: Z	(2)
$\sum_Z P(Y\|X,Z)\,P_X(Z)$	Rule 2: $(X \perp Y\|Z)_{G_{\underline{X}}}$	(3)
$\sum_Z P(Y\|X,Z)\,P(Z)$	Rule 3: $(X \perp Z)_{G_{\overline{X}}}$	(4)

Finally we get: $\sum_Z P(Y|X,Z)\,P(Z)$

Subgraph:

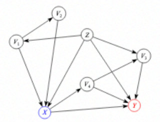
Show non-active nodes/edges




Fusion(β)
Summary
Treatment X
Outcome Y
Adjusted :
Query : $P_X(Y)$
Show More Details
Editor
Graphical
Structural
Refresh
1 <NODES>
2 X -90,90
3 Y 100,75
4 Z 0,-75
5 V_1 -150,-60
6 V_2 -60,-120
7 V_3 120,-30
8 V_4 0,30
9
14
V_2
V_1
Z
V_3
V_4
X
Y
Confounding Analysis
Admissible Sets
Admissibility Test
Instrumental Variables
IV Admissibility Test
Path Analysis
D-Separation
Causal Paths
Confounding Paths
Biasing Paths
Do-Calculus Analysis
Do-Inspector
Do-Separation
σ-Calculus Analysis
σ-Inspector

Compute The causal effect of X on Y conditional on with do : (Query: $P_X(Y)$ Non-Parametric Clear

1 $P_X(Y)$ is not identifiable from $P(V_1, V_2, V_3, V_4, X, Y, Z)$ and $P_X(V_1, V_2, V_3,$



Load

Remove

When things are identified, there are still arrows leading into Y.
What do we do with those?
How do you explain those relationships?

When things are identified, there are still arrows leading into Y. What do we do with those? How do you explain those relationships?

Outcomes have multiple causes. How do you justify that your proposed cause is the most causal factor?

Does every research question need an identification strategy?

Does every research question need an identification strategy?

No!

Correlation alone is okay!
Can lead to more focused causal questions later!

Forbes

BREAKING | Jan 14, 2022, 12:34pm EST | 145,393 views

Moderna Starts Human Trials Of mRNA Vaccine For Virus That Likely Causes Multiple Sclerosis

Robert Hart Forbes Staff

Business

I cover breaking news.

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TOPLINE Moderna recently launched early stage clinical trials for an mRNA vaccine against the Epstein-Barr virus (EBV), a common pathogen that infects almost everyone at some point in their lives, is the primary cause of mononucleosis and, according to a study published in the journal *Science* Thursday, likely causes multiple sclerosis (MS), offering hope the devastating neurological condition might be prevented.