

Causal inference is essential in science studies, yet many publications lack methods to substantiate causal claims. Structural causal models, often represented graphically with directed acyclic graphs, make causal assumptions transparent and improve communication. We illustrate the application with a hypothetical model of Open Science.

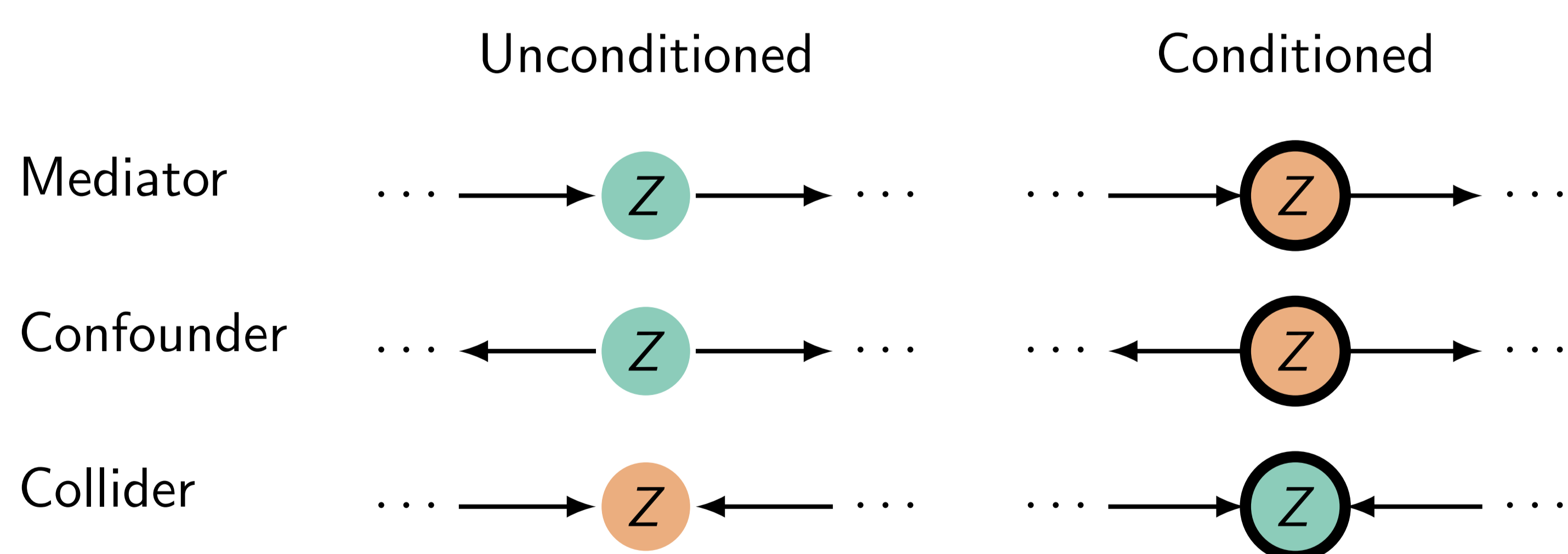
## Why causal thinking is important

- Predictive models often ill-suited to provide evidence for policy recommendations.
- Being explicit about causality can foster theoretical understanding.
- Transparency about causal assumptions helps communicate study limitations and can inform future studies.

## Causal inference with structural causal models

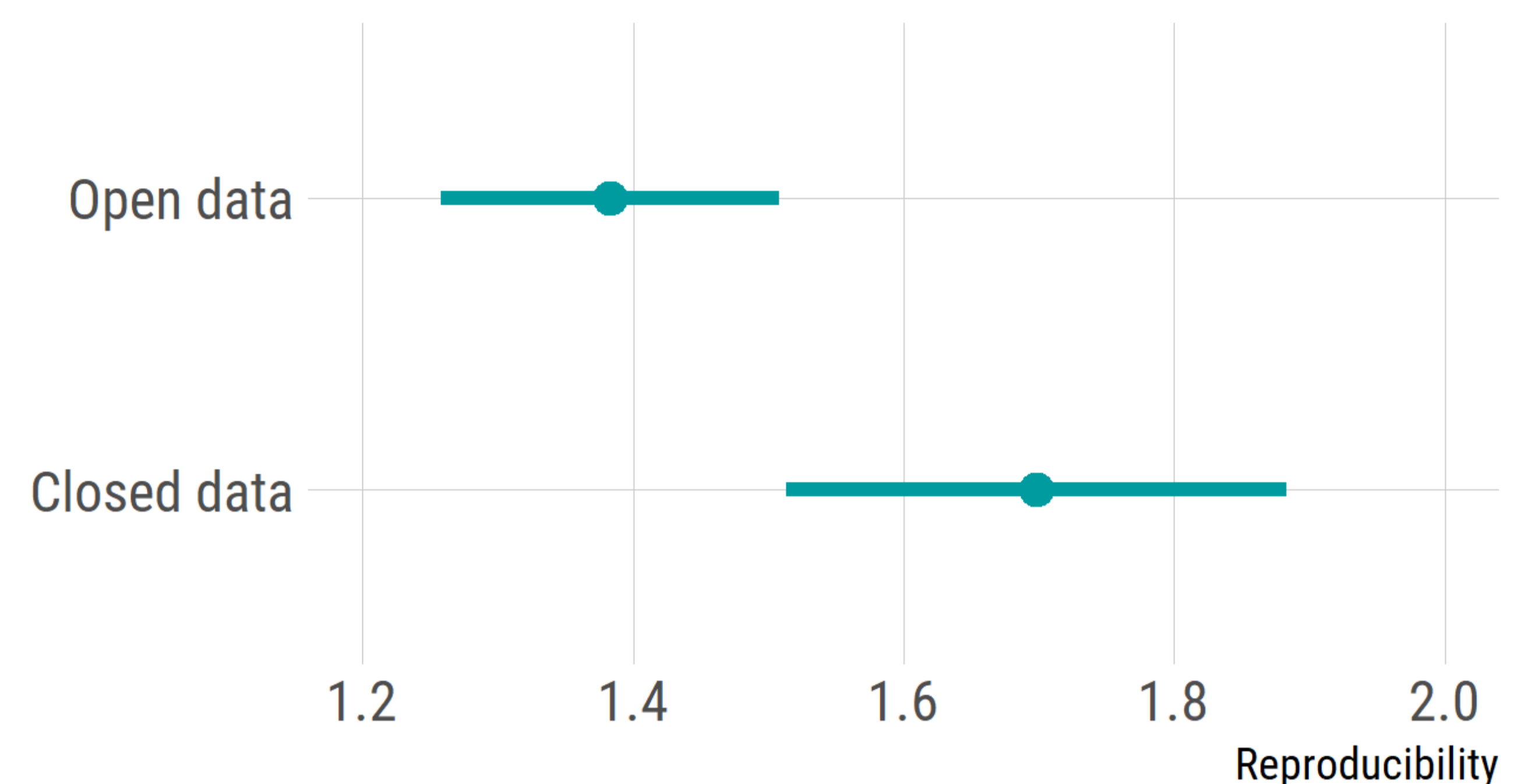
1. Develop a structural causal model, based on literature & domain expertise.
2. Test whether the assumed model is consistent with available evidence.
3. Use the assumed structural causal to understand how to identify causal effects.
4. Identified effects can be interpreted causally *under the assumed structural causal model*.

## Three types of variables in a Directed Acyclic Graph

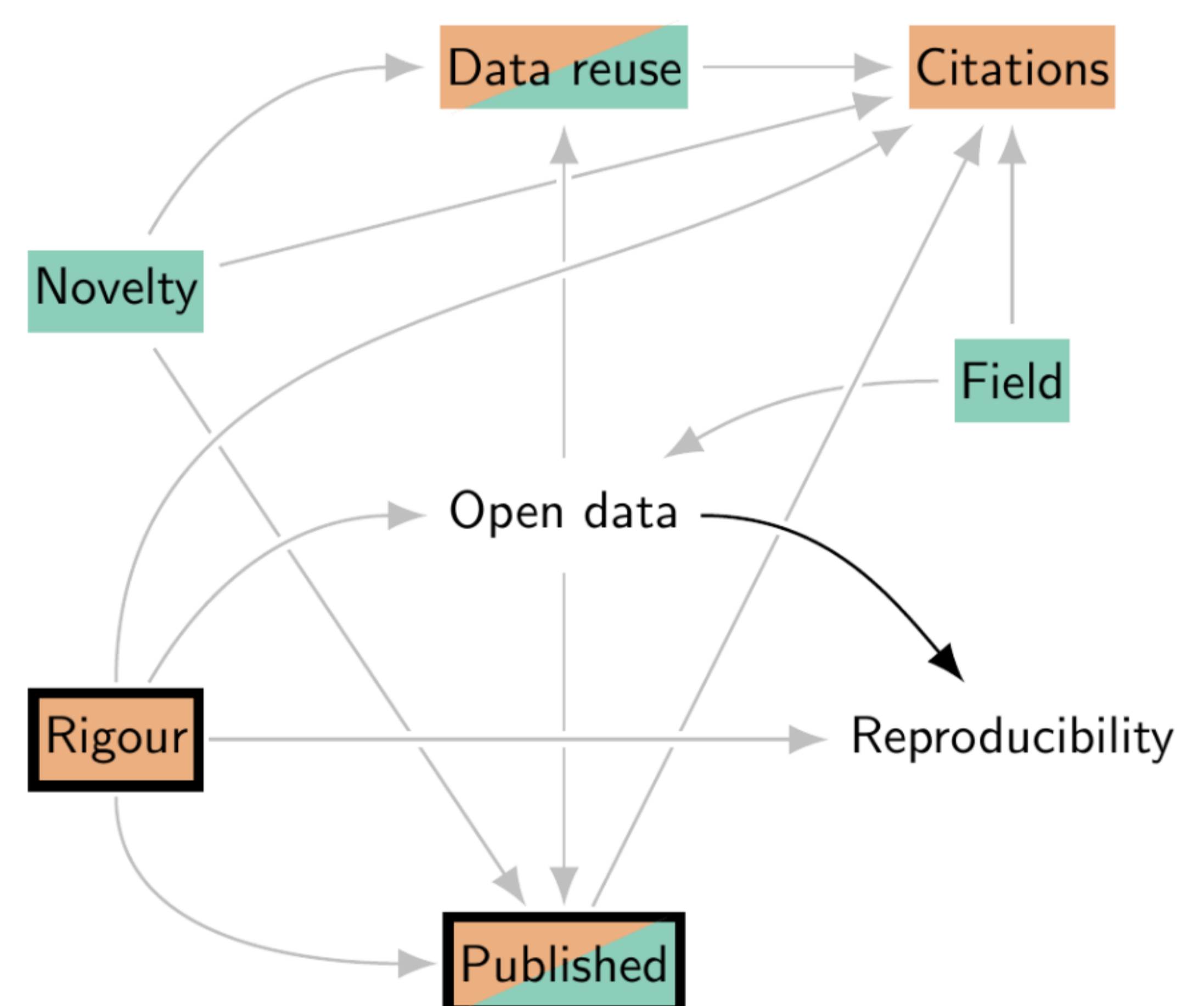


- A **confounder** does not represent a causal effect, and we usually want to control for it.
- A **collider** does not represent a causal effect, but we should not control for it.
- A **mediator** is part of a causal path, and we usually do not want to control for it.

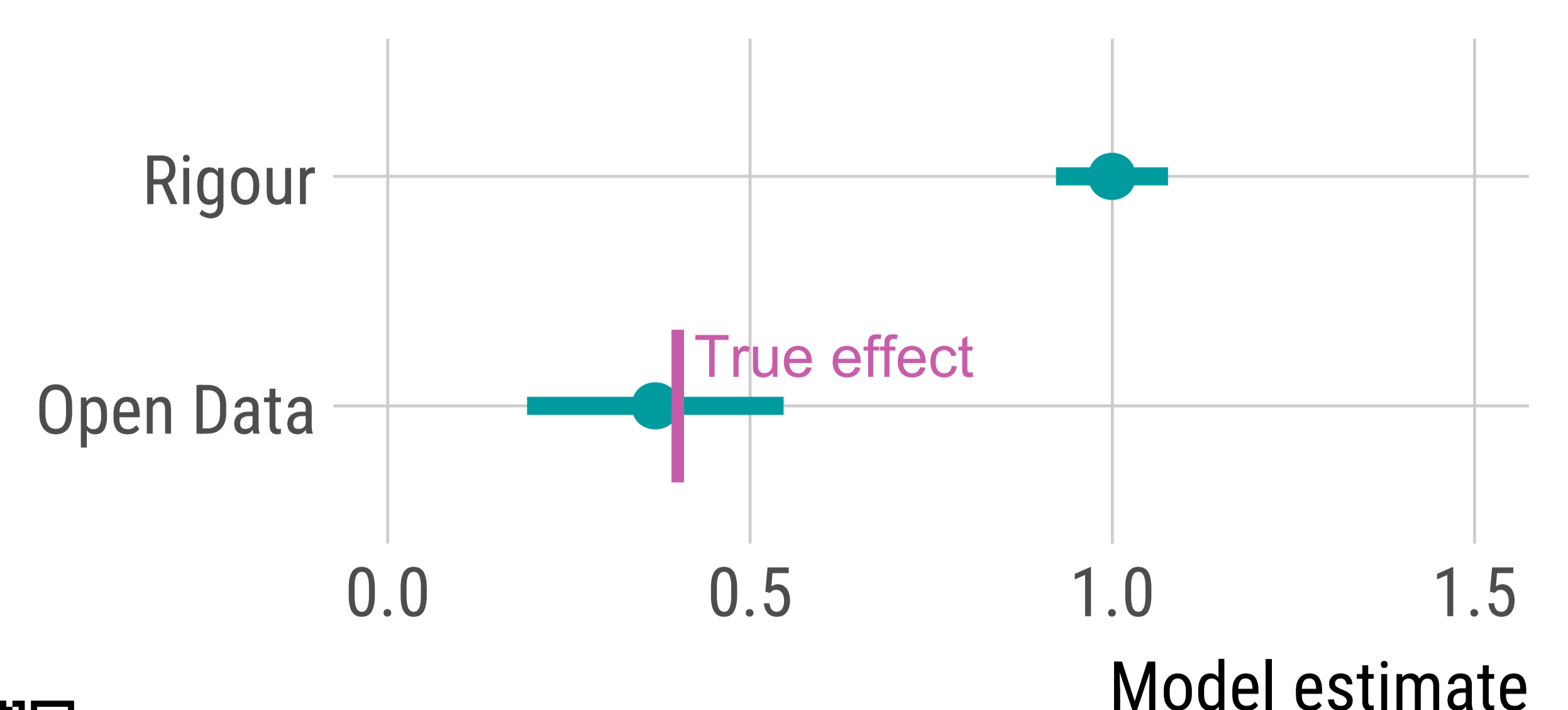
## Might Open Data lower research reproducibility?



Conditioning on a collider (*Published*) incorrectly suggests a negative effect of *Open Data* on *Reproducibility*.



Controlling for *Rigour* closes all non-causal paths and yields the correct positive estimate.



Klebel, Thomas, and Vincent Traag. 2024. "Introduction to Causality in Science Studies." SocArXiv. February 9. doi:10.31235/osf.io/4bw9e.