Causal inference is not just a statistics problem

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Causal Inference is not a statistics problem

Causal Inference is not *just* a statistics problem

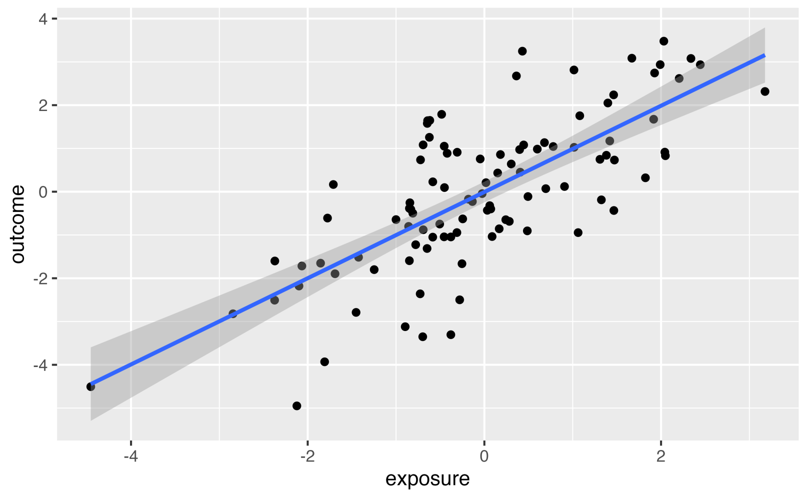
The problem

We have measured variables, what should we adjust for?

. . .

exposure	outcome	covariate
0.49	1.71	2.24
0.07	0.68	0.92
0.40	-1.60	-0.10
.	.	.
.	.	.
.	.	.

A bit more info




```r
cor(exposure, covariate)
```

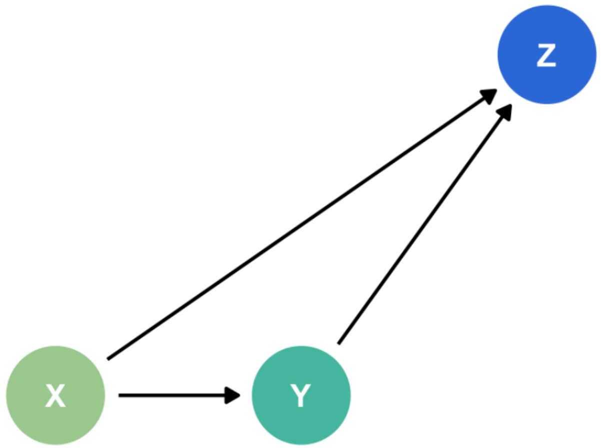
```
[1] 0.7
```

The exposure and measured factor are positively correlated

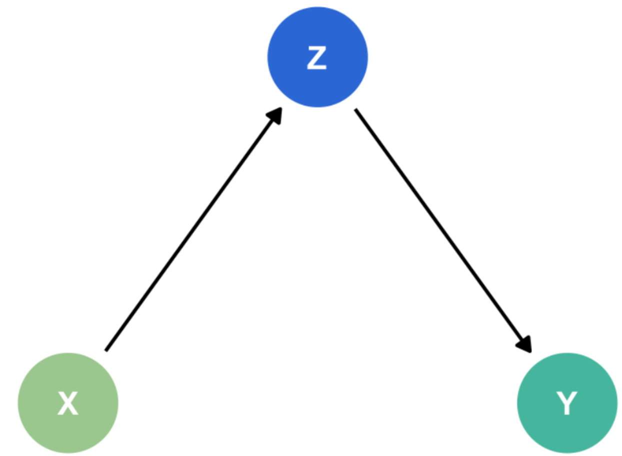
One unit increase in the exposure yields an average increase in the outcome of 1

To adjust or not adjust? That is the question.

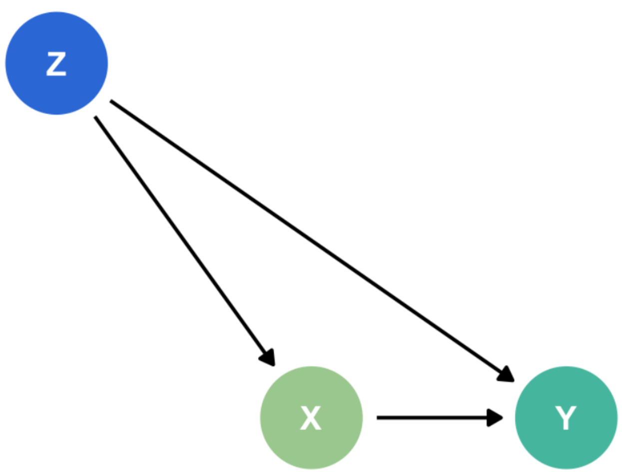
Causal Quartet



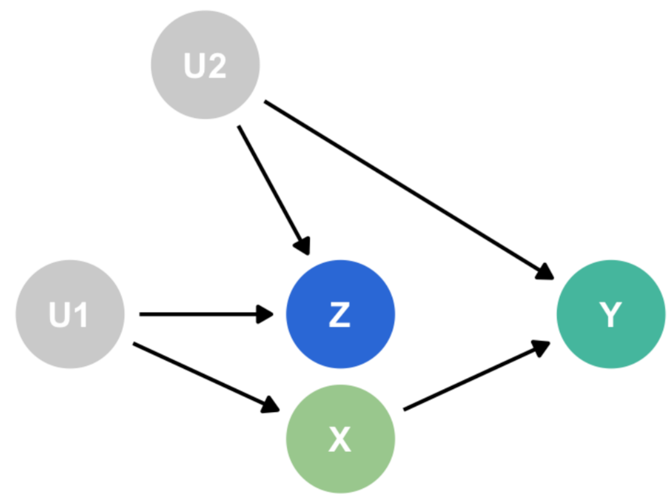
collider



Mediator



confounder



M-bias

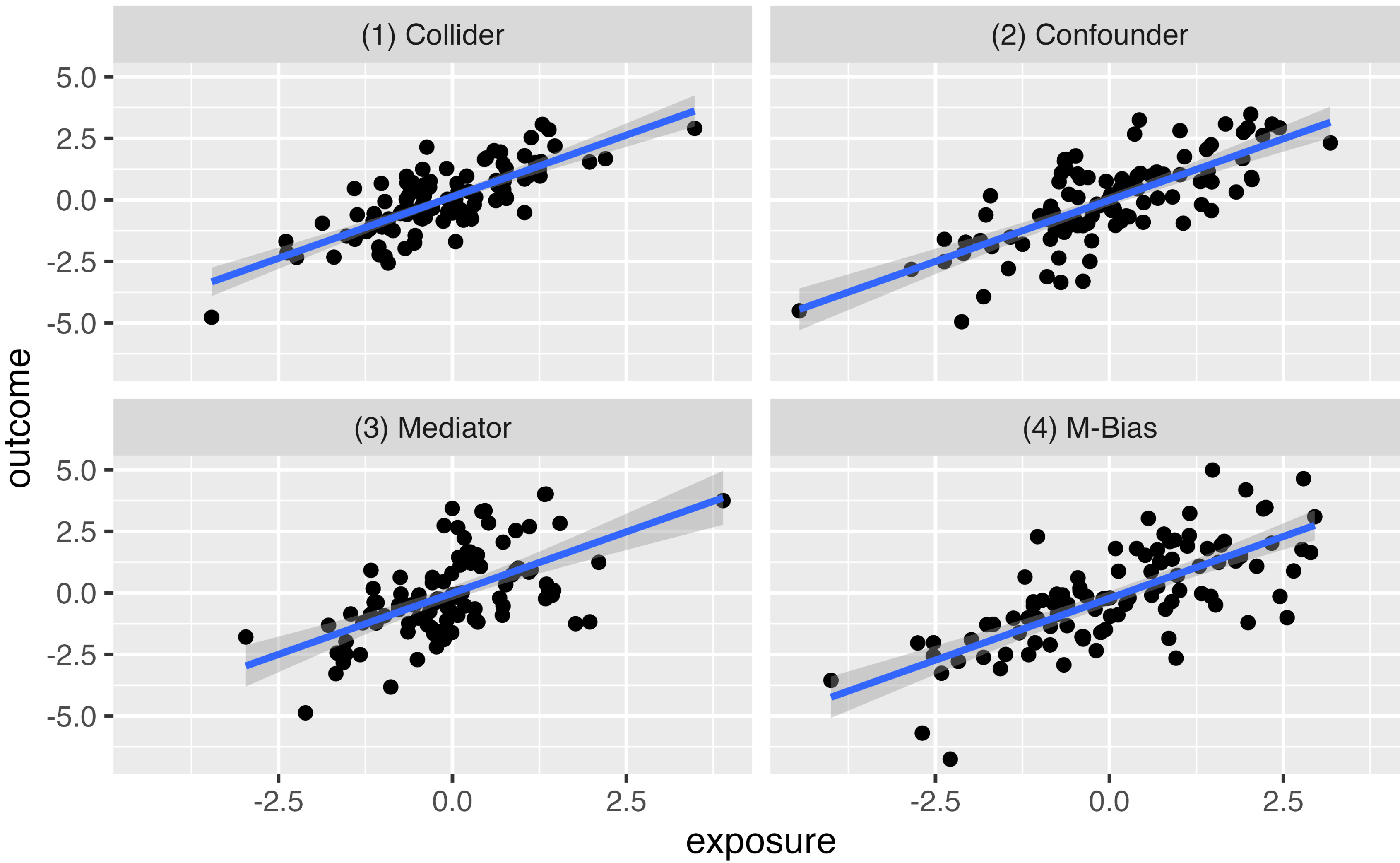
quartets

Your turn

- Install the `quartets` package: `install.packages("quartets")`
- For each of the following 4 datasets, look at the correlation between `exposure` and `covariate`: `causal_collider`, `causal_confounding`, `causal_mediator`, `causal_m_bias`
- For each of the above 4 datasets, create a scatterplot looking at the relationship between `exposure` and `outcome`
- For each of the above 4 datasets, fit a linear model to examine the relationship between the `exposure` and the `outcome`

10:00

Relationship between exposure and outcome



Relationship between exposure and covariate

```r
causal_quartet |>
  group_by(dataset) |>
  summarise(cor(exposure, covariate))
```

```
# A tibble: 4 × 2
  dataset         `cor(exposure, covariate)`
  <chr>                                <dbl>
1 (1) Collider                         0.700
2 (2) Confounder                       0.696
3 (3) Mediator                         0.696
4 (4) M-Bias                           0.696
```

Correct effects

Table 1: Correct causal models and causal effects for each data-generating mechanism. The notation $X; Z$ implies that we should adjust for Z when estimating the causal effect. In other words, for the confounder data generating mechanism and direct effect mediator model, the potential outcomes are independent of exposure given the observed factor Z.

Data generating mechanism	Correct causal model	Correct causal effect
(1) Collider	Y ~ X	1
(2) Confounder	Y ~ X ; Z	0.5
(3) Mediator	Direct effect: Y ~ X ; Z	Direct effect: 0
	Total Effect: Y ~ X	Total effect: 1
(4) M-Bias	Y ~ X	1

D'Agostino McGowan L, Gerke T, Barrett M (2023). Causal inference is not a statistical problem. Preprint arXiv:2304.02683v1.

Observed effects

Table 2: Coefficients for the exposure under each data generating mechanism depending on the model fit as well as the correlation between X and Z.

Data generating mechanism	ATE not adjusting for Z	ATE adjusting for Z	Correlation of X and Z
(1) Collider	1	0.55	0.7
(2) Confounder	1	0.50	0.7
(3) Mediator	1	0.00	0.7
(4) M-Bias	1	0.88	0.7

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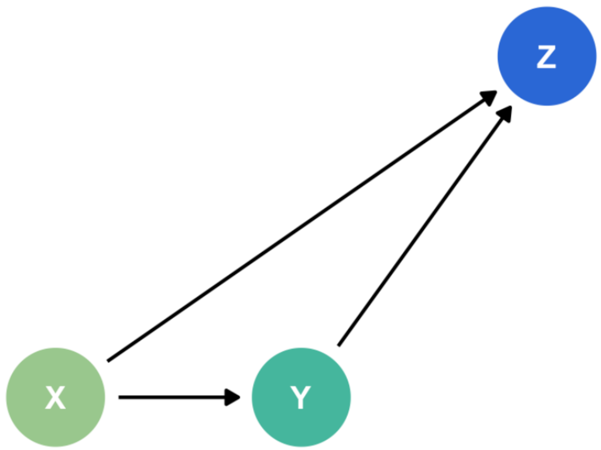
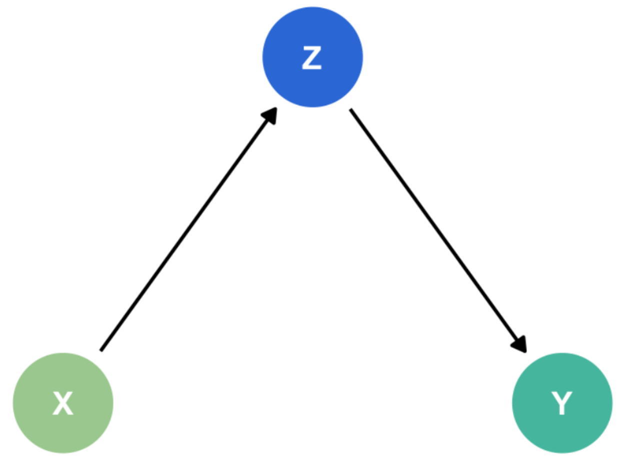
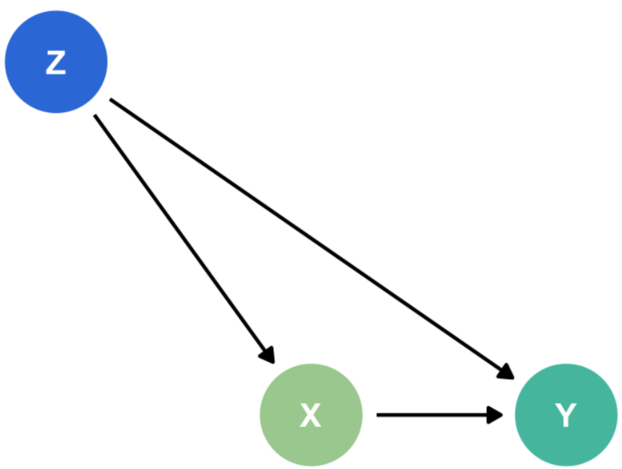
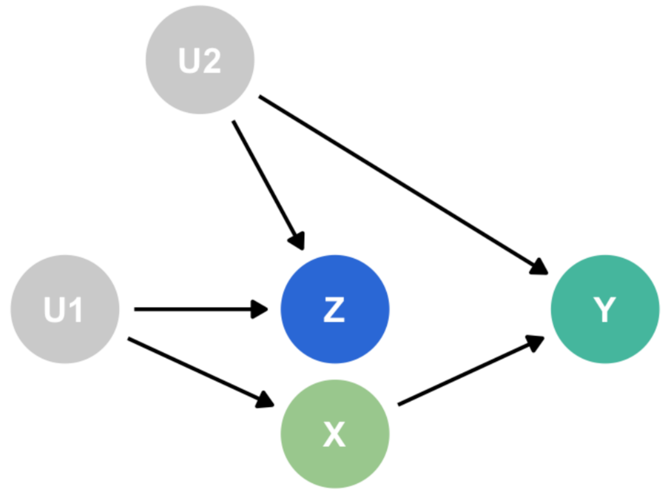
The solution







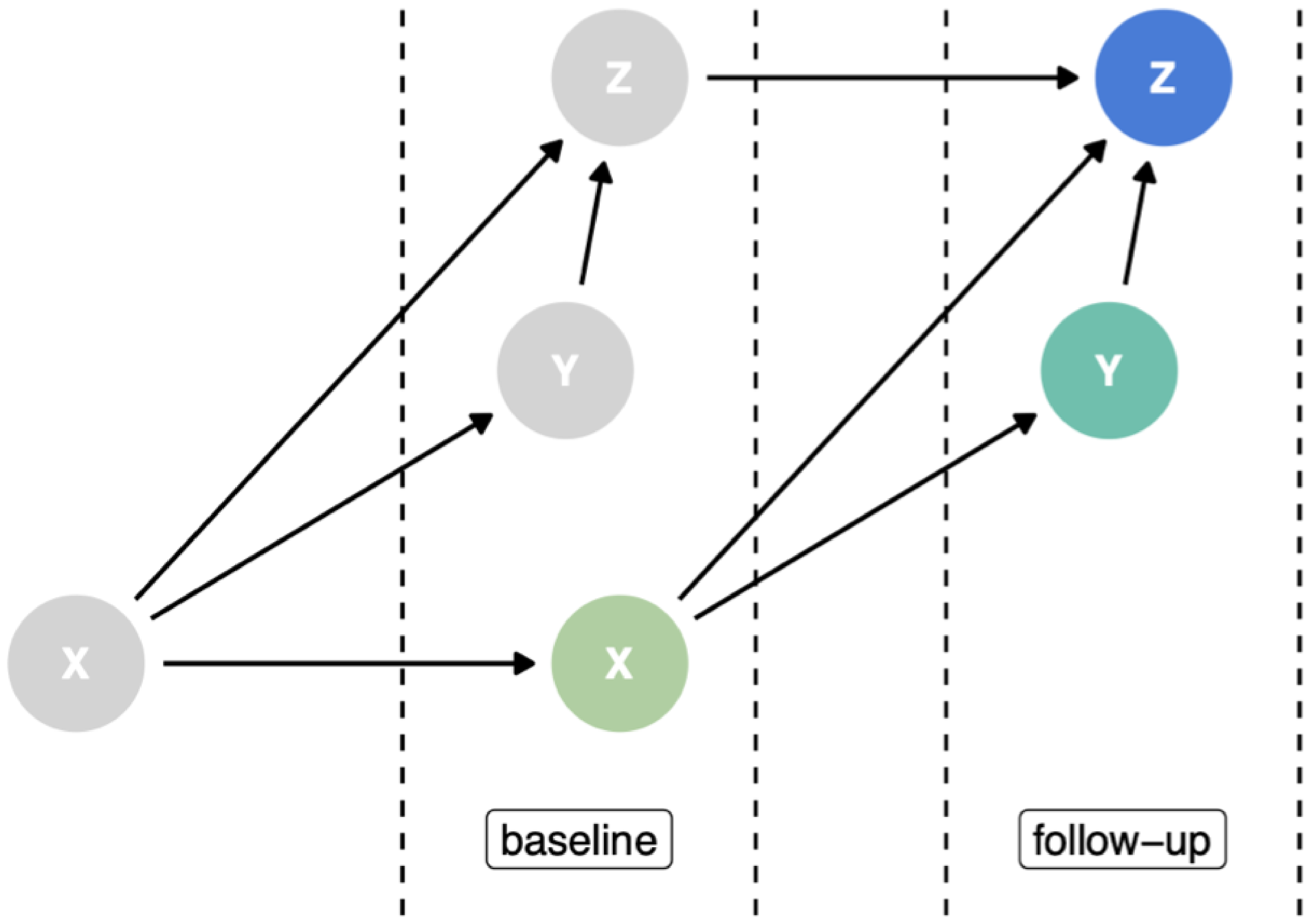


The *partial* solution

```
# A tibble: 100 × 6
   exposure_baseline outcome_baseline covariate_baseline exposure_followup
               <dbl>            <dbl>              <dbl>             <dbl>
 1          -1.43             0.287            -0.0963            -1.53
 2           0.0593          -0.978            -1.11              -0.278
 3           0.370            0.348             0.647             -0.00464
 4           0.00471          0.851             0.755             -0.806
 5           0.340            1.94              1.19              -0.276
 6          -3.61            -0.235            -0.588             -5.29
 7           1.44            -0.827            -1.13               1.52
 8           1.02            -0.0410            0.689              1.12
 9          -2.43            -2.10             -1.49              -3.94
10          -1.26            -2.41             -2.78              -0.442
# ℹ 90 more rows
# ℹ 2 more variables: outcome_followup <dbl>, covariate_followup <dbl>
```

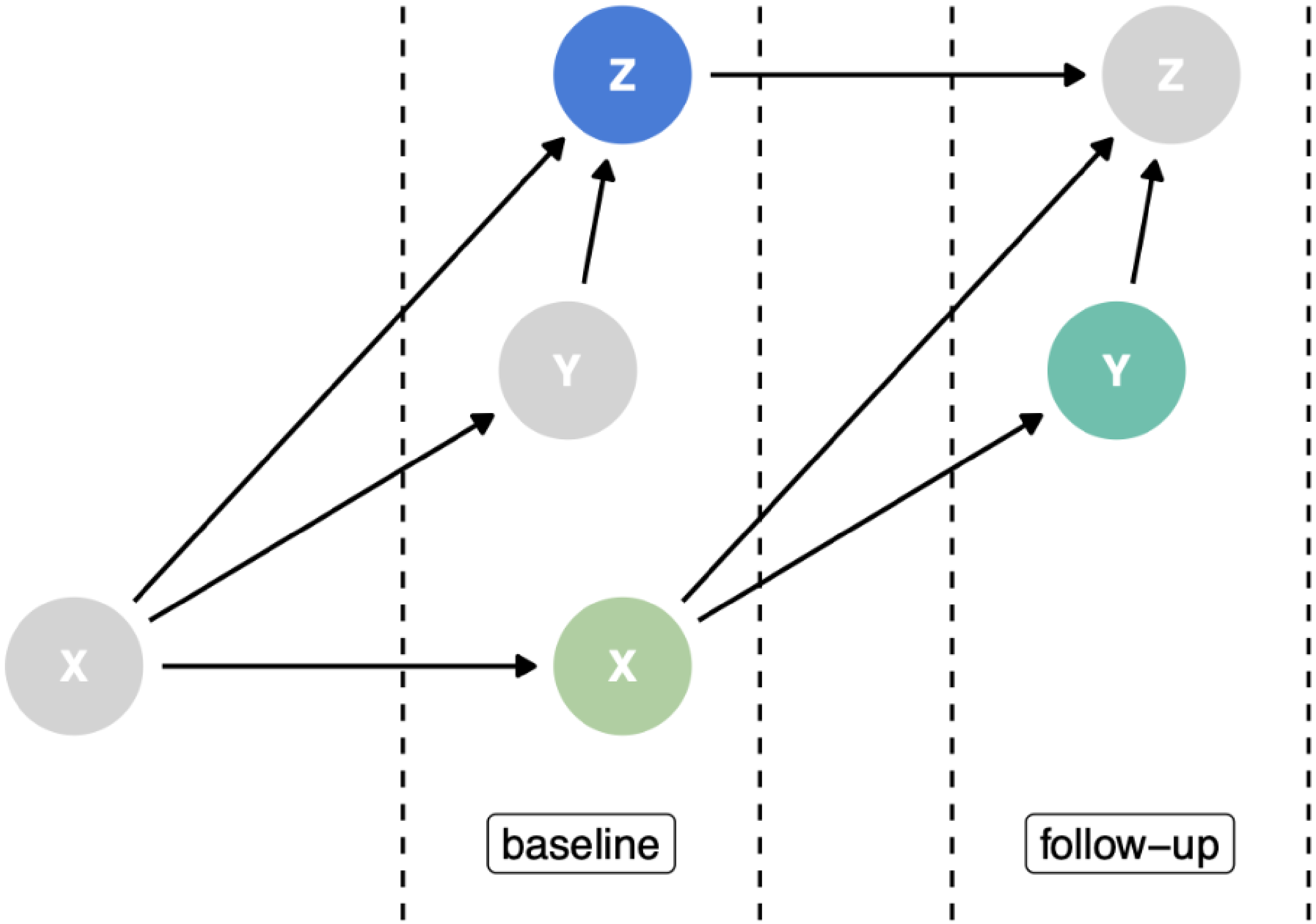
Time-varying data

Time-varying DAG



True causal effect: 1 **Estimated causal effect**: 0.55

Time-varying DAG



True causal effect: 1 Estimated causal effect: 1

```
outcome_followup ~ exposure_baseline +
covariate_baseline
```

The *partial* solution

Table 3: Coefficients for the exposure under each data generating mechanism depending on the model fit as well as the correlation between X and Z.

Data generating mechanism	ATE not adjusting for pre-exposure Z	ATE adjusting for pre-exposure Z	Correct causal effect
(1) Collider	1	1.00	1.0
(2) Confounder	1	0.50	0.5
(3) Mediator	1	1.00	1.0
(4) M-Bias	1	0.88	1.0

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On M-Bias

- The relationship between Z and the unmeasured confounders needs to be really large (Liu et al 2012)

- “To obsess about the possibility of [M-bias] generates bad practical advice in all but the most unusual circumstances” (Rubin 2009)

- There are (almost) no true zeros (Gelman 2011)

- Asymptotic theory shows that induction of M-bias is quite sensitive to various deviations from the exact M-Structure (Ding and Miratrix 2014)

Your turn

- For each of the following 4 datasets, fit a linear linear model examining the relationship between `outcome_followup` and `exposure_baseline` adjusting for `covariate_baseline`: `causal_collider_time`, `causal_confounding_time`, `causal_mediator_time`, `causal_m_bias_time`

10:00