IV as research design

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I'll now tell the second story of instrumental variables (IV).

The key concepts are **causality** and **research design**.

I will explain what *research design* means, and assume that you already have a good understanding of what *causality* is (even though we have not discussed it formally)

- Defining causality formally is very hard. Indeed, there is no universal definition that everyone agrees on.
- Instead, researchers in different fields simply rely on the definitions of causality that they find acceptable for their own work.

Research design

Definition of Research design: a plan or framework for conducting a study that aims to test a specific hypothesis or answer a question.

A good research design involves answers to:

1. What is the *causal relationship* of interest?
2. What is the *(quasi-)experiment* that could ideally be used to capture the causal effect of interest?
3. What is your *identification* strategy?
4. What is your mode of *statistical inference*?

Q1: What is the causal relationship of interest?

- A **causal relationship** is useful for making predictions about the consequences of changing circumstances or policies:
  - it tells us what would happen in *alternative* (or *counterfactual*) worlds
- Eg: suppose you are interested in investigating human capital
  - the causal effect of *schooling* on wages: the increment to wages an individual would receive if he or she got more schooling (Card, 1999)
  - the causal effect of *class size* on wages (Angrist and Lavy, 1999)

An ideal experiment

- The most credible and influential research designs use *random assignment*.
- Suppose we are interested in a causal "if-then" question:
  - **Do hospitals make people healthier?**
- One empirical method is to compare the health status of *those who have been to the hospital* to *those who have not*.

Data from National Health Interview Survey (NHIS)

Group	Sample Size	Mean health status	Std. Error
Hospital	7,774	2.79	0.014
No Hospital	90,049	2.07	0.003

Taken at face value, this result suggests that **going to the hospital makes people sicker**.

Data from National Health Interview Survey (NHIS)

```
Group         Sample Size     Mean health status     Std. Error
Hospital         7,774              2.79                0.014
No Hospital      90,049             2.07                0.003
```

- However, the two groups (`Hospital`, `No Hospital`) are not comparable:
- Even if after hospitalization **people who have sought medical care** are not as healthy as **those who were never hospitalized**, they may be better off than they otherwise would have been.

This is a standard example where researchers should rely on (quasi-)experimental data instead of observational data to make causal claims.

Treatments and potential outcomes

- Think about **hospital treatment** as a binary random variable:

$$D_i \in \{0, 1\}.$$

- The outcome is Y_i. For any individual there are two **potential outcome** variables:

$$\text{Potential outcom } = \begin{cases} Y_{1i} & \text{if } D_i = 1; \\ Y_{0i} & \text{if } D_i = 0. \end{cases}$$

The observed outcome Y_i is Y_{0i} if $D_i = 1$ or otherwise Y_{1i}.

The **observed difference in average health between two groups**, $E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0]$, can be decomposed into two parts:

- $E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 1]$ ($= E[Y_{1i} - Y_{0i} \mid D_i = 1]$)
  - *Average treatment effect* (ATE) on the treated
- $E[Y_{0i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]$
  - *Selection bias*

The **causal effect** we are interested in:

- $E[Y_{1i} - Y_{0i}]$, the (unconditional) *average treatment effect*

Random Assignment Solves the Selection Problem

- *Random assignment* of D_i solves the selection problem as it makes D_i independent of potential outcomes.

  1. ATE on the treated is the same as the unconditional ATE: $E[Y_{1i} - Y_{0i} \mid D_i = 1] = E[Y_{1i} - Y_{0i}]$.
  2. No selection bias: $E[Y_{0i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0] = 0$.

- Notable proponents of this method are Banerjee and Duflo, who won the Nobel prize in 2019 for the usage of Randomized Controlled Trials in policy evaluations.

IV solves the Selection Problem

- If the causal effect of interest forbids experiments, another approach is to use IV.
- Again, identifying whether Z (college distance, school construction, birthdat quarter) is a valid IV requires detailed institutional knowledge.

Main lesson: know your estimand and use DAG for your research design.

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  - We economists even invented the term *"endogeneity"* specifically for this problem.

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  - We economists even invented the term *"endogeneity"* specifically for this problem.
- In practice, the ideal way to estimate the effects of D_i on Y_i is to **make the assignment of D_i random**
  - That is, making D_i independent of potential outcomes.
  - D_i is *treatment*, say **hospitalization** or **schooling**
  - Y_i is *potential outcome*, say **health status** or **wage**

Random assignment

Under random assignment:

- $E[Y_{1i} \mid D_i = 1] = E[Y_{1i}]$
- $E[Y_{0i} \mid D_i = 0] = E[Y_{0i}]$

And the (unconditional) *average treatment effect* is simply the diff:

$$E[Y_{1i} - Y_{0i}] = E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0]$$

Random assignment as benchmark

Random assignment is an experimental method and generally cannot be used in economics.

- Economics is not an experimental science (yet).

However, random assignment can be viewed as the benchmark for other quasi-experimental tools widely used in economics:

- IV
- Difference-in-Differences
- (fuzzy) Regression Discontinuity
- Synthetic Control, Matching, etc ...

A causal model

Consider the *causal model* $Y_i = \beta_0 + \beta_1 X_i + U_i$, where

- U_i's are unobserved
- X_i and U_i may be correlated.
  - That is, the assignment of X_i may be non-random.

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Two remarks:

1. This is a causal model. NOT a regression or machine learning model.
2. I recommend the post "Why Econometrics is Confusing", where the author explains THREE distinct meanings of the seemingly simple linear model $Y_i = \beta_0 + \beta_1 X_i + U_i$.

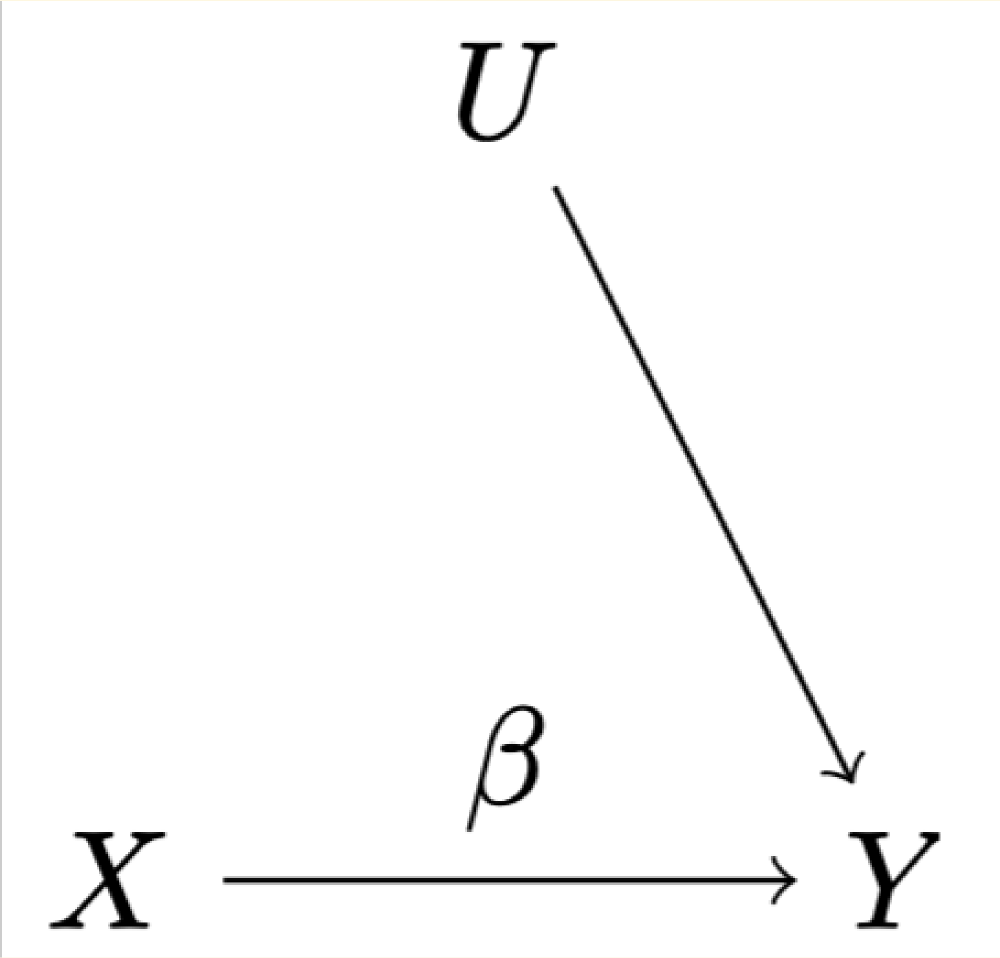
IV as research design

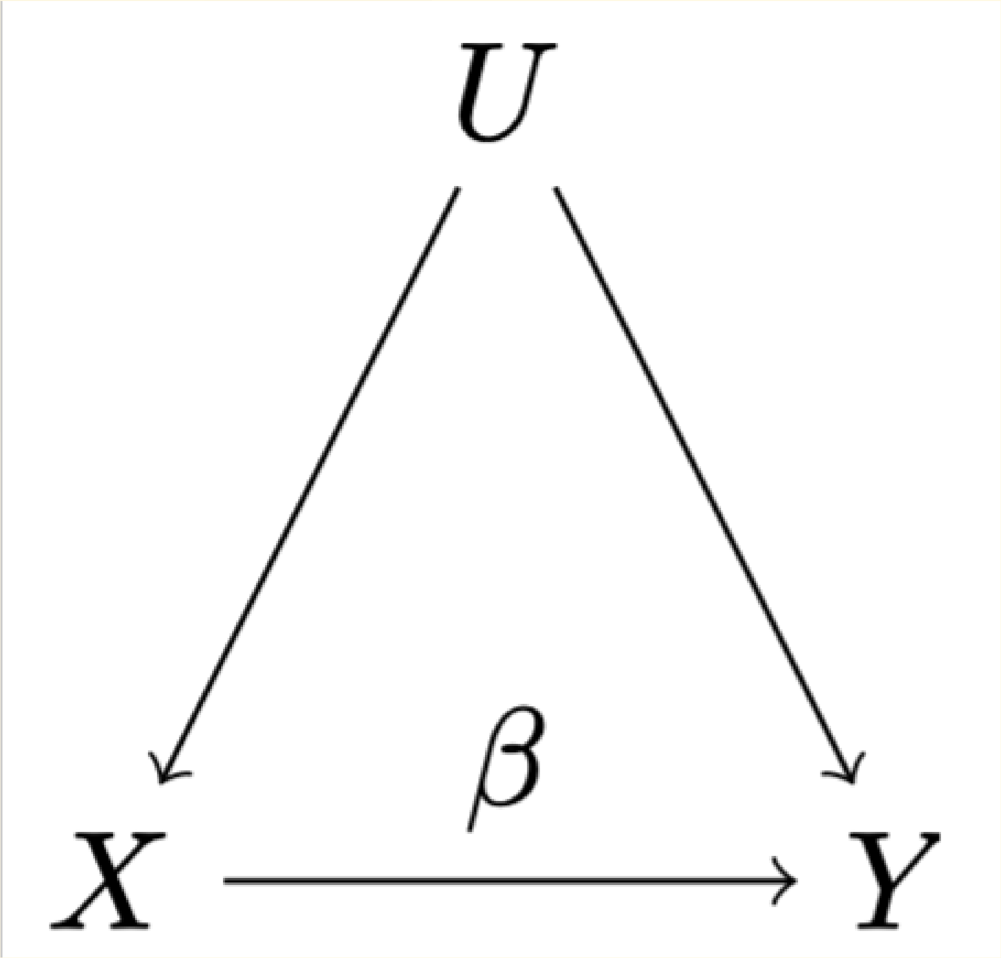
We state the three properties of good IVs from the *research design perspective*.

Z is a valid IV for the causal model if the following restrictions hold:

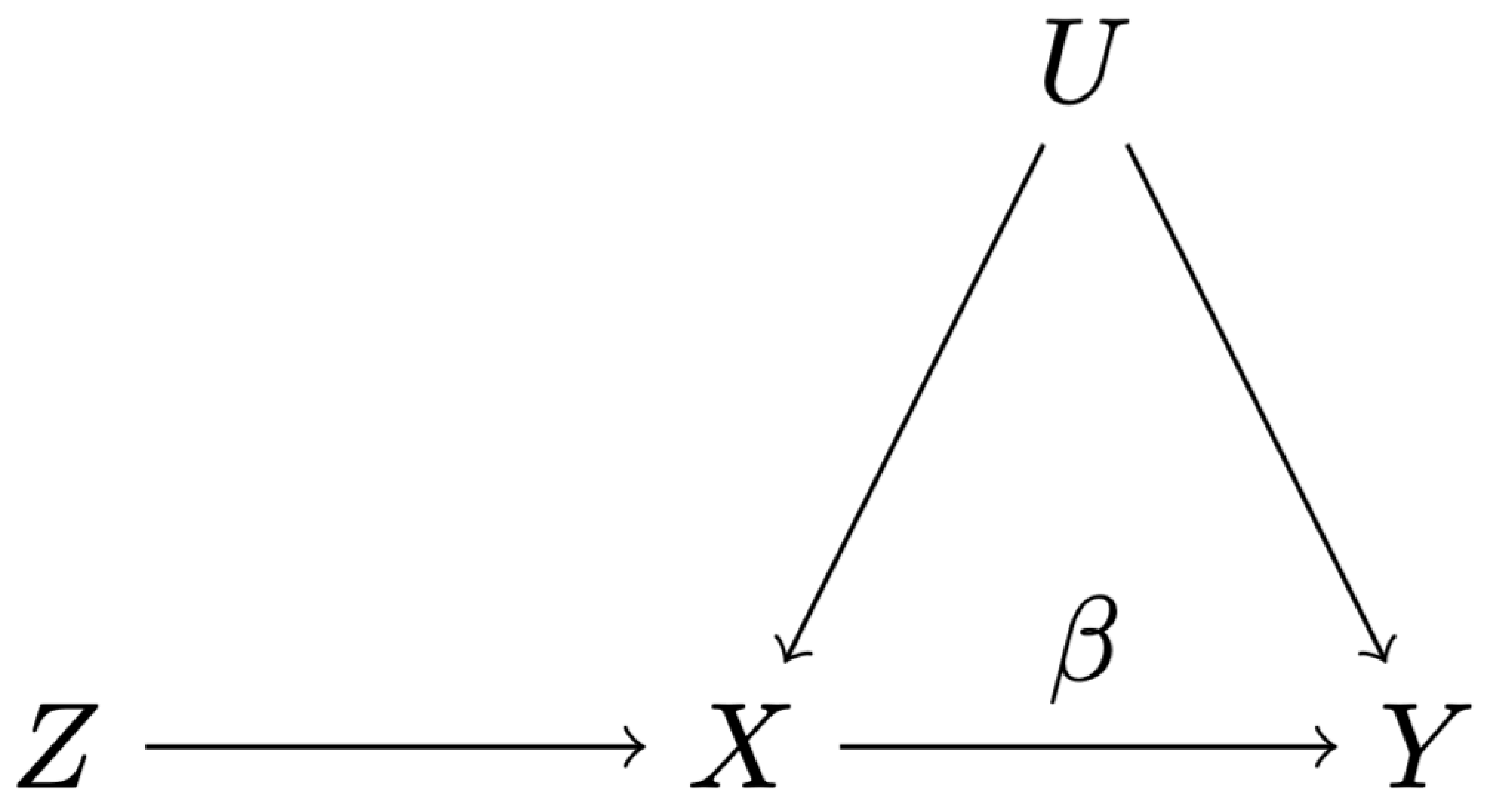
- **Relevance.** Z_i directly affects X_i.
  - That is, $Z \rightarrow X$.
- **Exclusion**. Z_i affects Y_i *only through* X_i and not through U_i.
  - That is, $Z \not\rightarrow U$. Or, equivalently, the "assignment" of Z_i is independent of U_i.
- **As-good-as-random assignment.** All individuals face the same distribution of Z_i.
  - That is, $U \not\rightarrow Z$.

Random assignment & non-random assignment

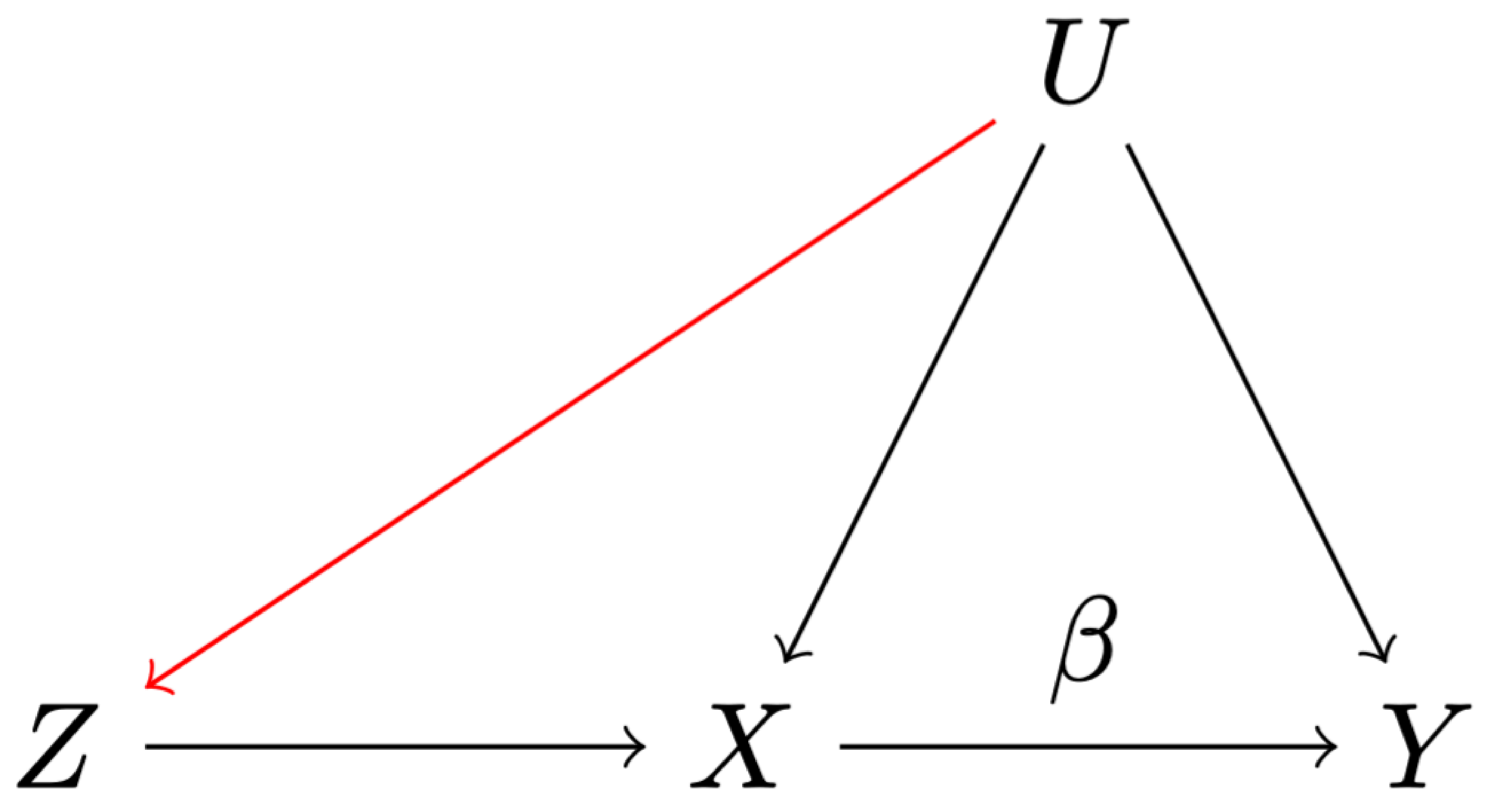




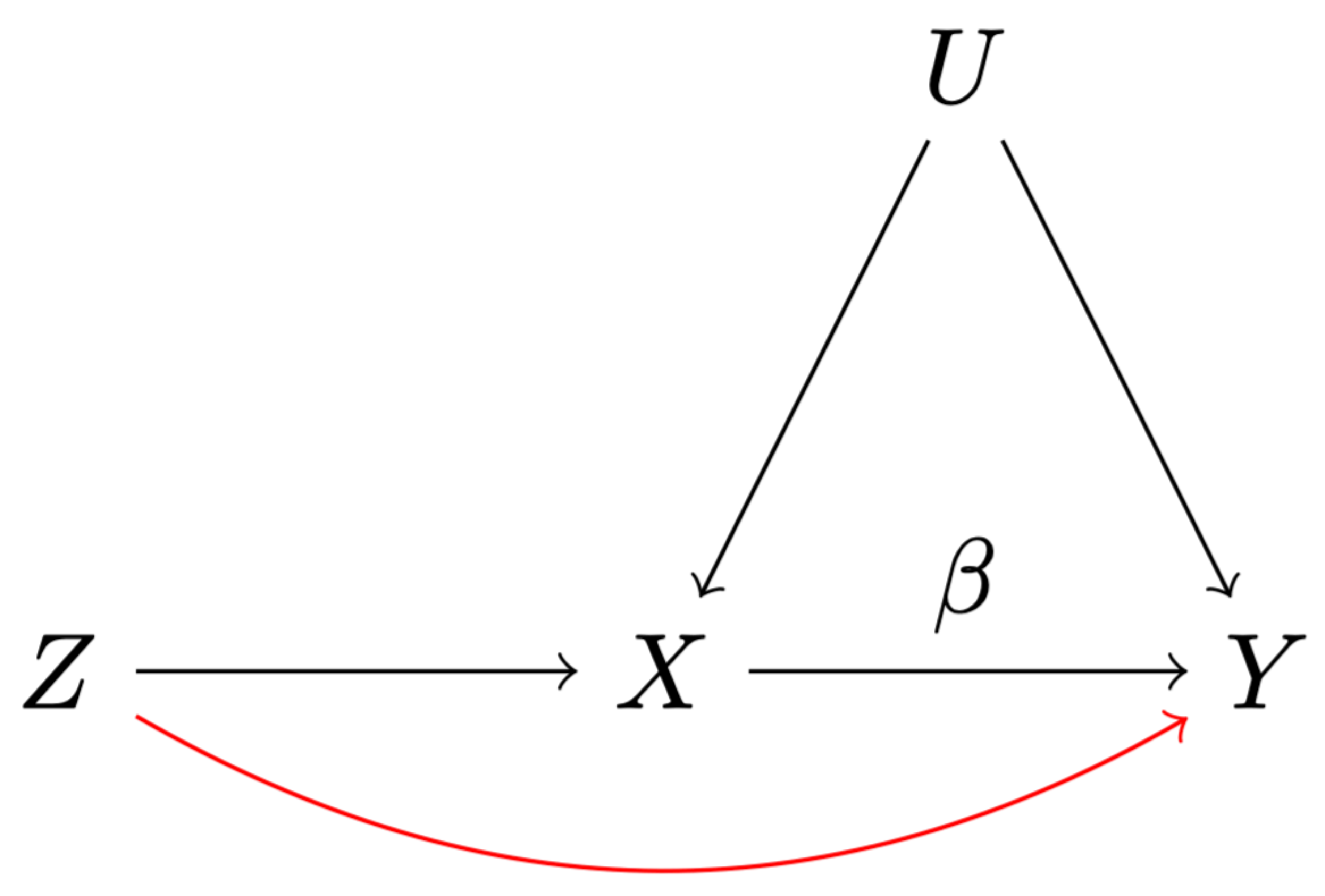
A valid instrument



Violation of "As-Good-As-Random Assignment"



Violation of "Exclusion"



- Older texts sometimes refer to $cov(Z_i, U_i) = 0$ as the exclusion restriction.
- Modern IV texts distinguish between the two cases.
  - The difference should be obvious based on the DAGs.
- Indeed, the statement $cov(Z_i, U_i) = 0$ is purely regression-based, and cannot be used directly in a causality-based study.