USAID
FROM THE AMERICAN PEOPLE

# Causal Modeling

USAID MENA Advanced MEL Workshop

# Session Objectives

- Understand USAID practice around causal modeling
- Introduce new analytical developments that can extend USAID practice of causal modeling and link it to impact evaluation and learning agendas
- Identify management opportunities to incorporate best practice and new trends into activity implementation

# Level Set

How does USAID do causal modeling?

- ADS 201
- How-To Note: Developing a Project Logic Model
- Technical Note: The Logical Framework
- In Defense of Logic Models

# Logic Model

- A graphic or visual depiction of a theory of change that illustrates the connection between what a strategy, project, or activity will do and what it hopes to achieve
- There are a wide range of logic models
  - Results Framework
  - LogFrame
  - Causal loop diagram

# Results Framework

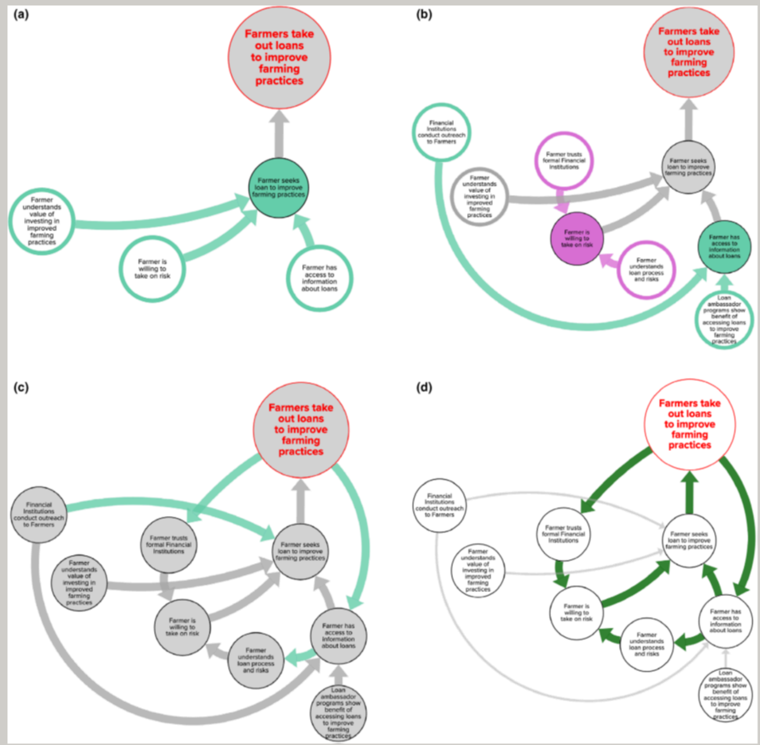
- A type of logic model representing the development hypothesis of a USAID mission's strategy
- Diagrams the causal links between the strategy's Goal, Development Objectives (DOs), and Intermediate Results (IRs)
- Explicates theory of change, aids strategic planning, and serves as a communications tool

# LogFrame

- Complements the CDCS Results Framework by carrying the development hypothesis through from the overall program/project to the supporting activities
- Replicates the causal linkages, but starting from a Development Objective and ending with activity inputs
- Defines exactly what resources are needed to achieve results

# Causal Loop Diagram

- A logic model that emphasizes feedback loops and includes notation for polarity of relationshpis




Understanding Smallholder Access to Finance, USAID/Uganda Feed the Future Market System Monitoring Activity

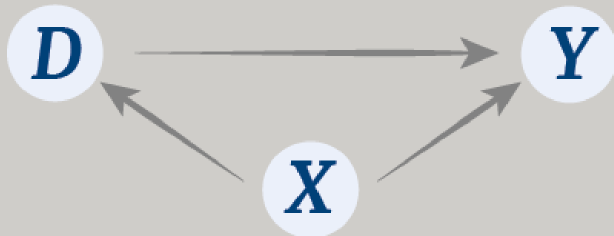
# New Directions

Directed Acyclic Graphs (DAGs)

- A logic model with probabilities attached
- Causal influence revealed through ancestor/descendant relationships
- Directed = one way only!
- Acyclic = no feedback loops! Arrows cannot backtrack

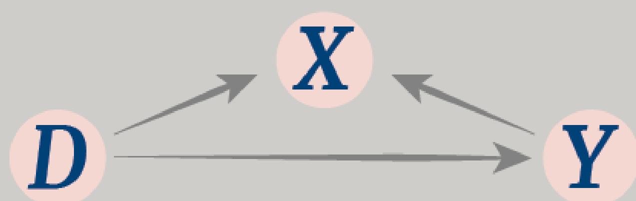
# The Four Confounds

## The Fork

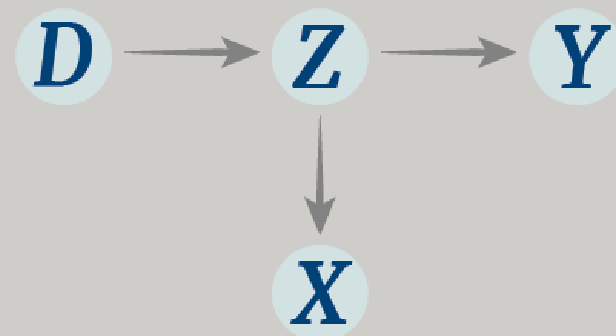



## The Pipe


## The Collider

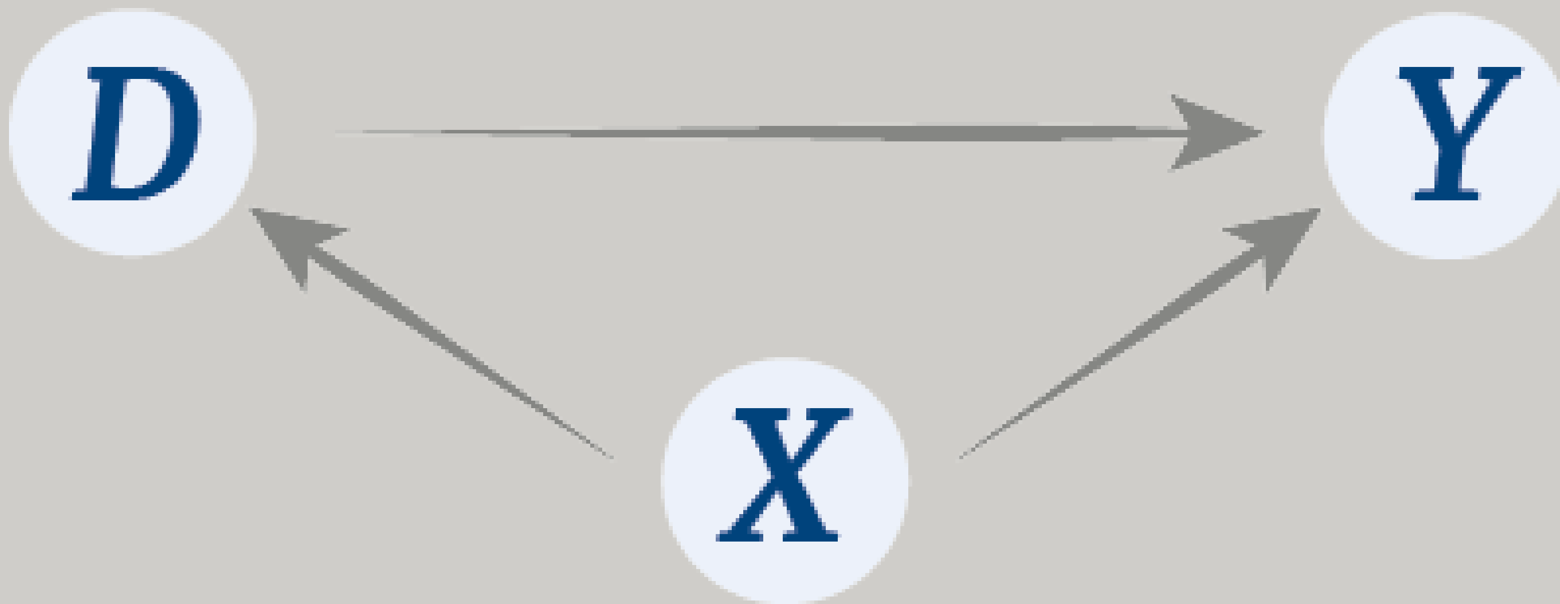



## The Descendant




McElreath, Richard. *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*. 2nd ed.

# The Fork




- X causes both treatment and outcome
- Must control for X (backdoor criterion)

$D$ is NOT $\perp\!\!\!\perp$ $Y$

$D \perp\!\!\!\perp Y \mid X$

# Solve for the Fork

The fork is the most common problem researchers face

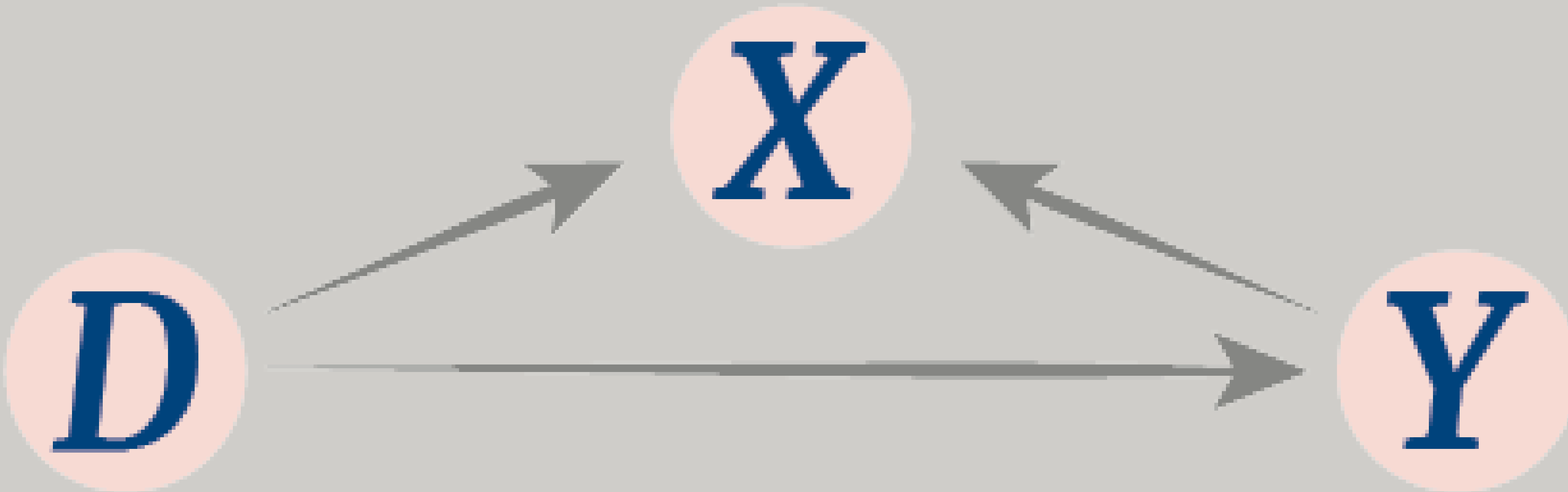
- All adjustment or matching methods attempt to solve the fork
  - Regression adjustment
  - Propensity score matching
  - Inverse probability weighting

## The Pipe


- X is a post-treatment outcome
- Knowledge, Skills, Attitude, Practices
- DO NOT control for X !!

$D \perp\!\!\!\perp Y$

# The Collider

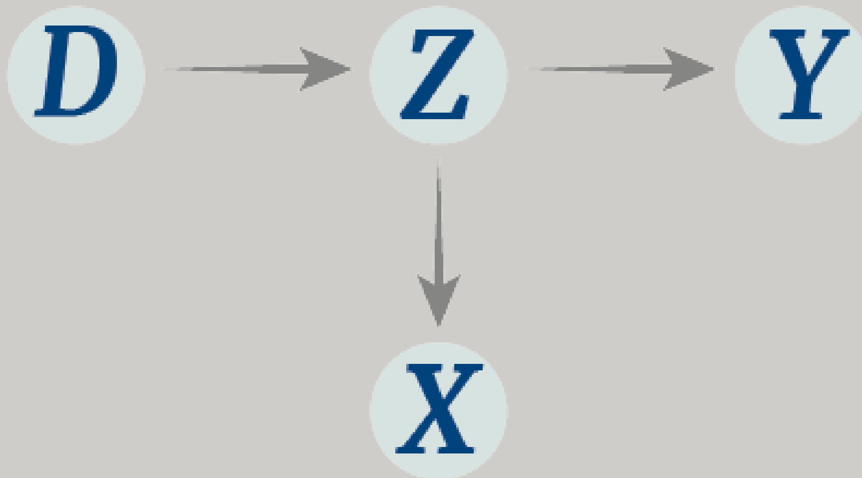



- DO NOT control for X !!

$D \perp\!\!\!\perp Y$

$D$ IS NOT $\perp\!\!\!\perp Y \mid X$

# The Descendant




- Z is not a post-treatment outcome, but a downstream unmeasured confounder
- Control for proxy variable X
- If X a strong enough proxy:

$$D \perp\!\!\!\perp Y \mid X$$

# Latent Variables

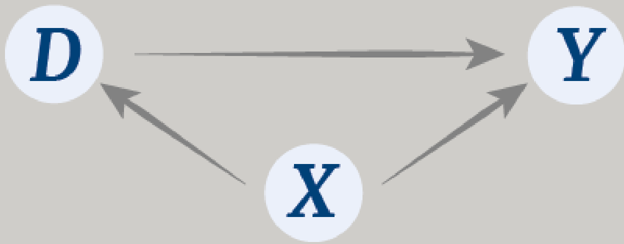
- DAGs can include unmeasured or hidden (latent) variables
- Allows for other advanced analytical methods
  - Structural equation modeling
  - Latent class analysis
  - Factor analysis

# Evaluation Designs as DAGs

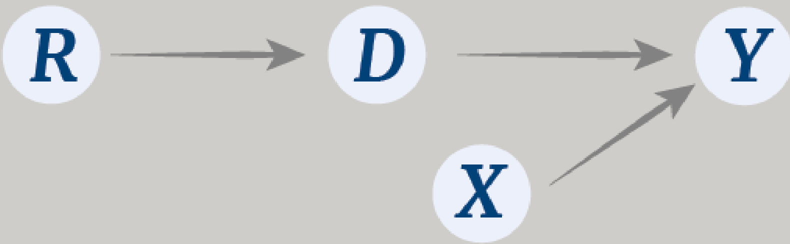
- Randomized Controlled Trial (RCT)
- Instrumental Variables estimation (IV)
- Regression Discontinuity (RD)

# Randomized Controlled Trial

## Unmeasured confounder of treatment and outcome

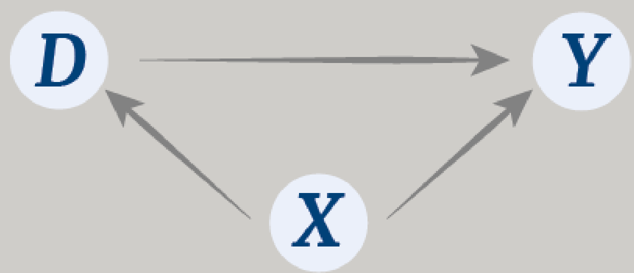



## Randomization of treatment

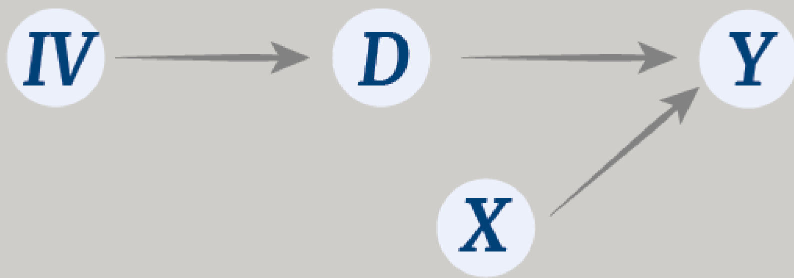


# Instrumental Variables Estimation

## Unmeasured confounder of treatment and outcome

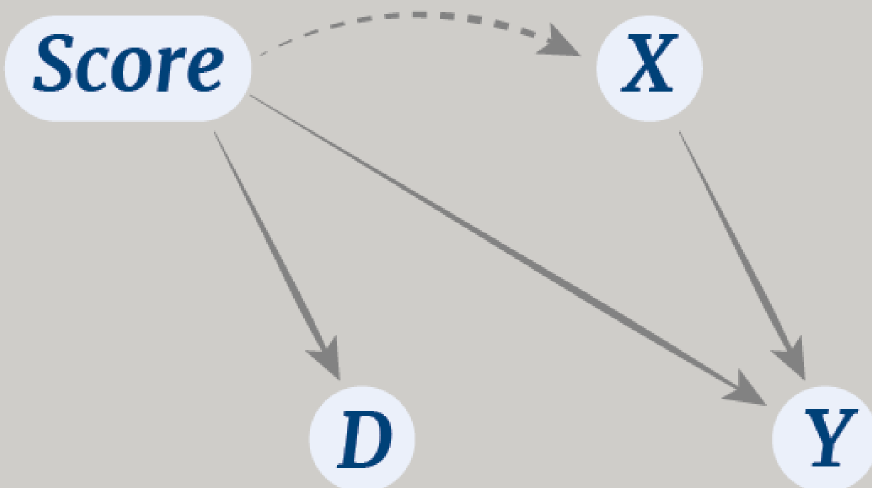



## Randomization through instrument

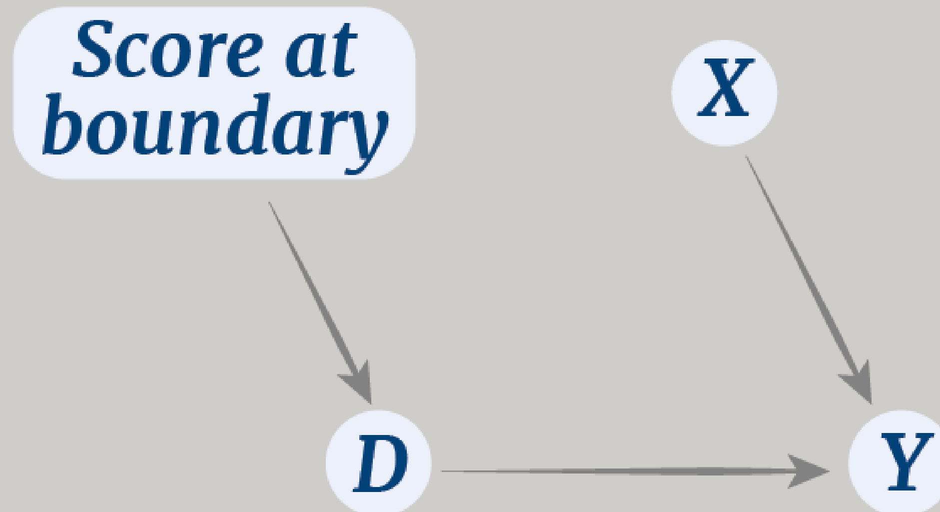


# Regression Discontinuity

**Score variable allocates treatment**




**Boundary imposes randomization**




Cunningham, Scott. *Causal Inference: The Mixtape*.

# Recap

- Logic modeling can be extended to methods such as causal loop diagrams or directed acyclic graphs
- These methods enable the integration of assumptions and hypotheses with data
- USAID must continue to push the boundary of causal modeling and link them to analytical methods

# Looking forward

- Stay tuned for sessions on learning agendas, mapping, and Bayesian analysis
- We will attach probabilities to our causal models

Thank you!