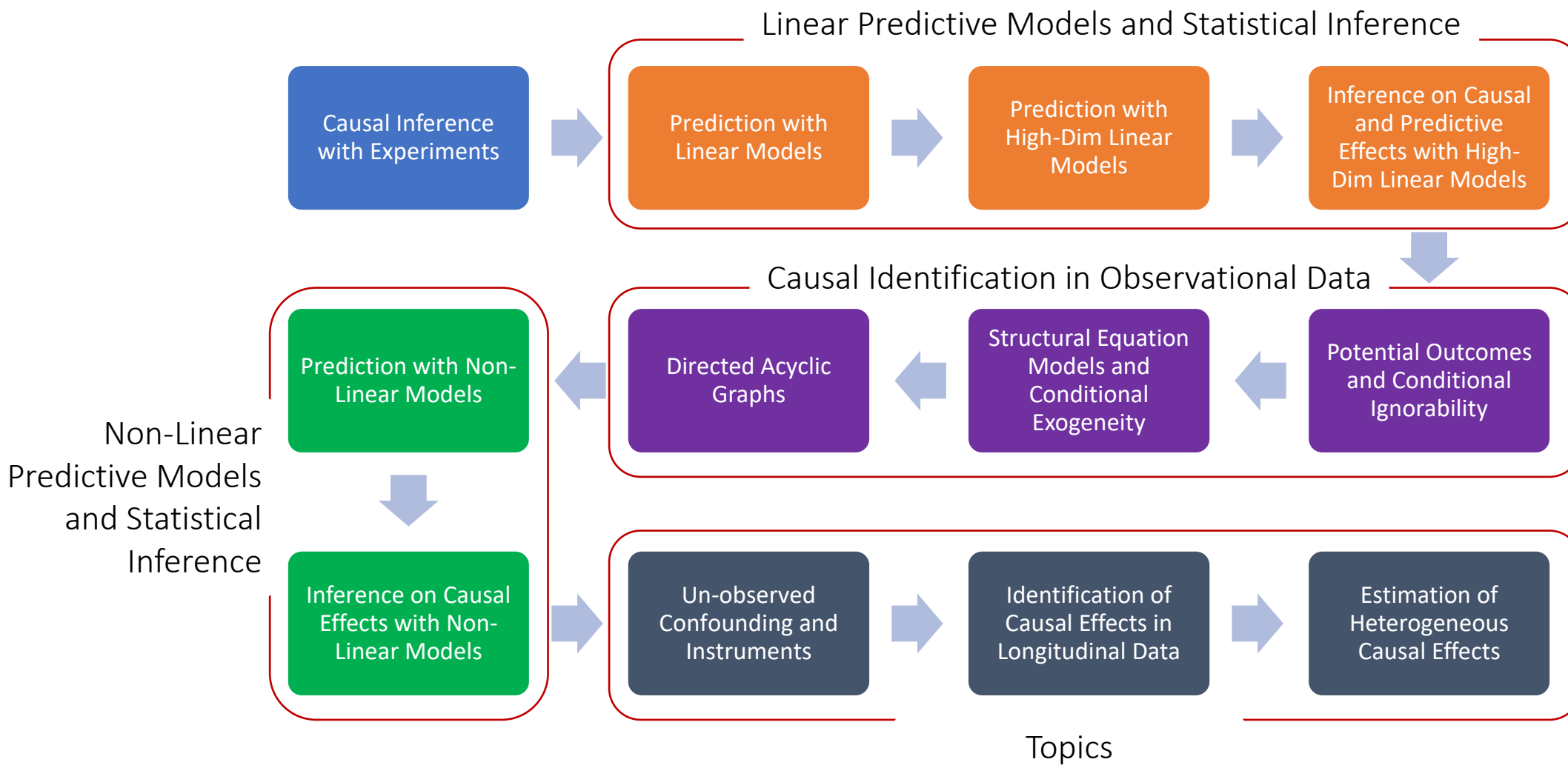
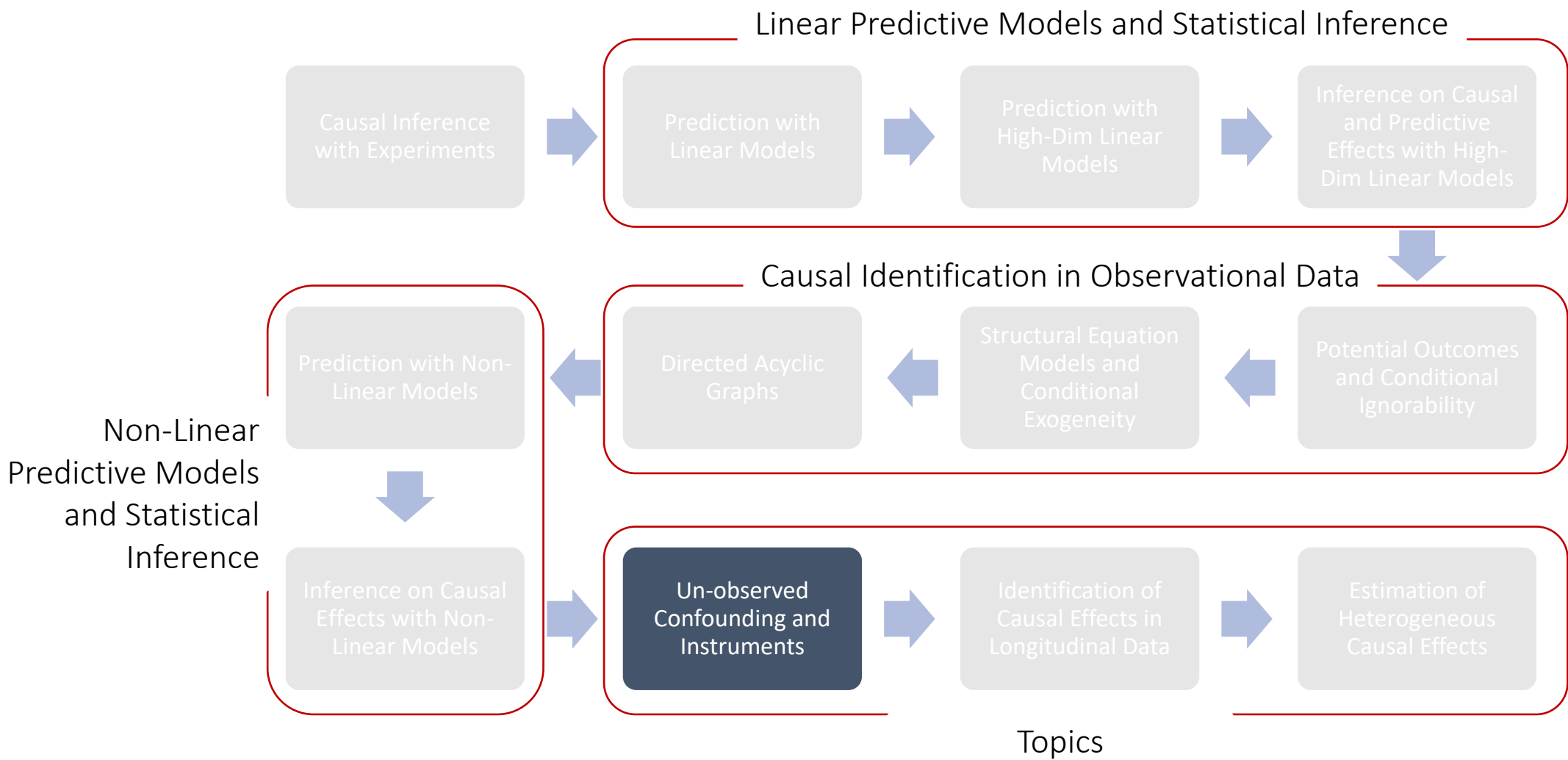


# MS&E 228: Unobserved Confounding

Vasilis Syrgkanis

MS&E, Stanford



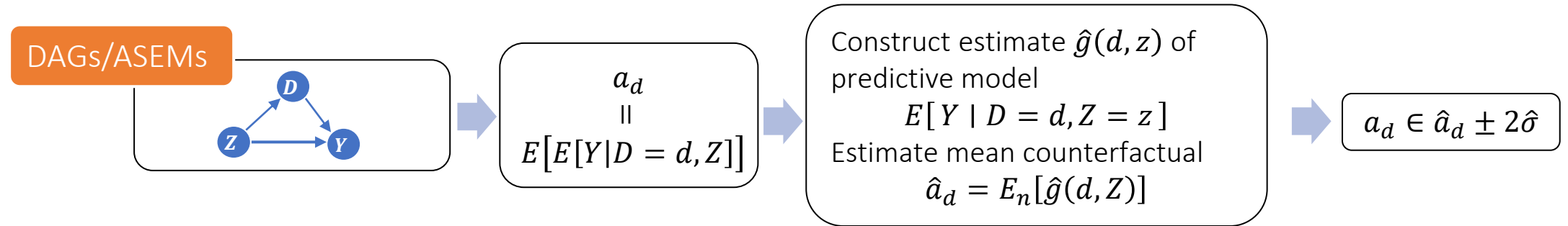


# Goals for Today

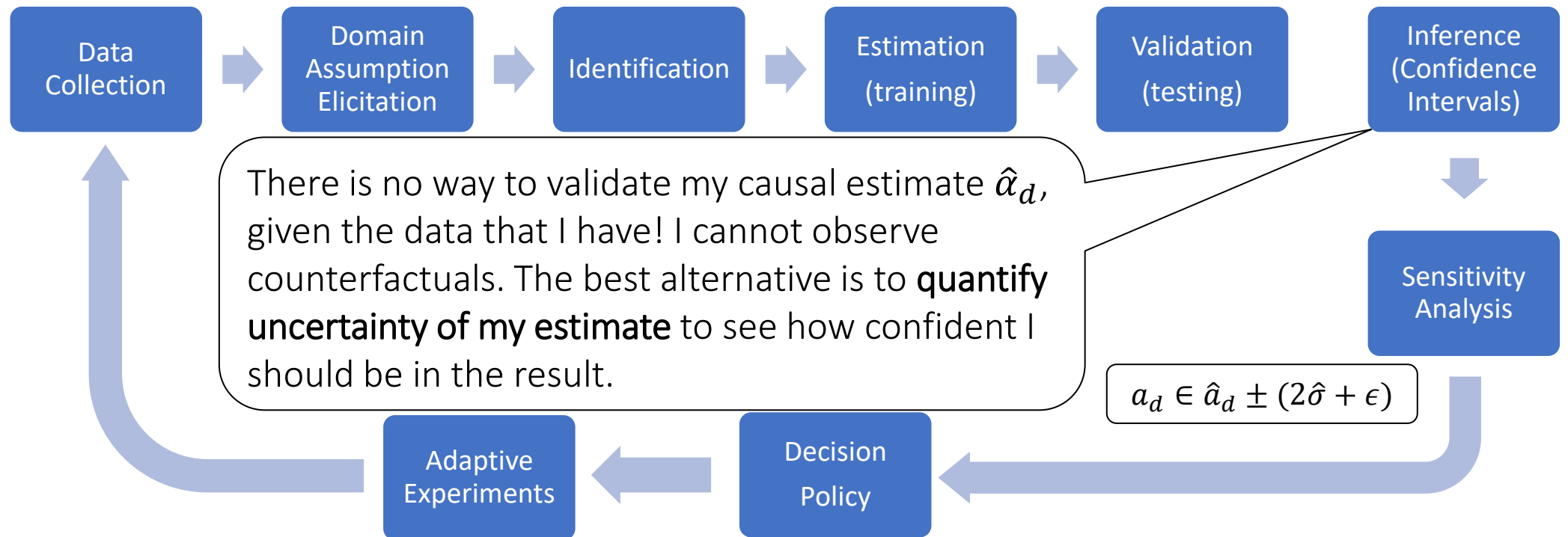
- What can we do when we have un-observed confounding
- Omitted variable bias bounds
- Introduction to “Instruments”

# Causal Inference Pipeline

Theory

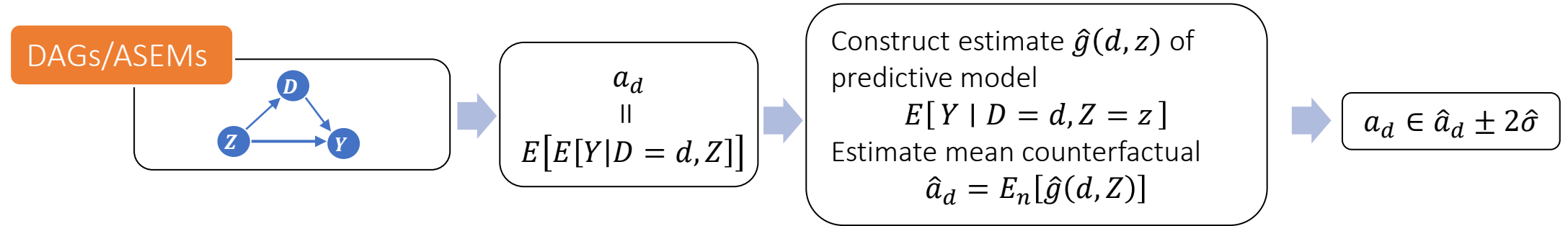


Practice

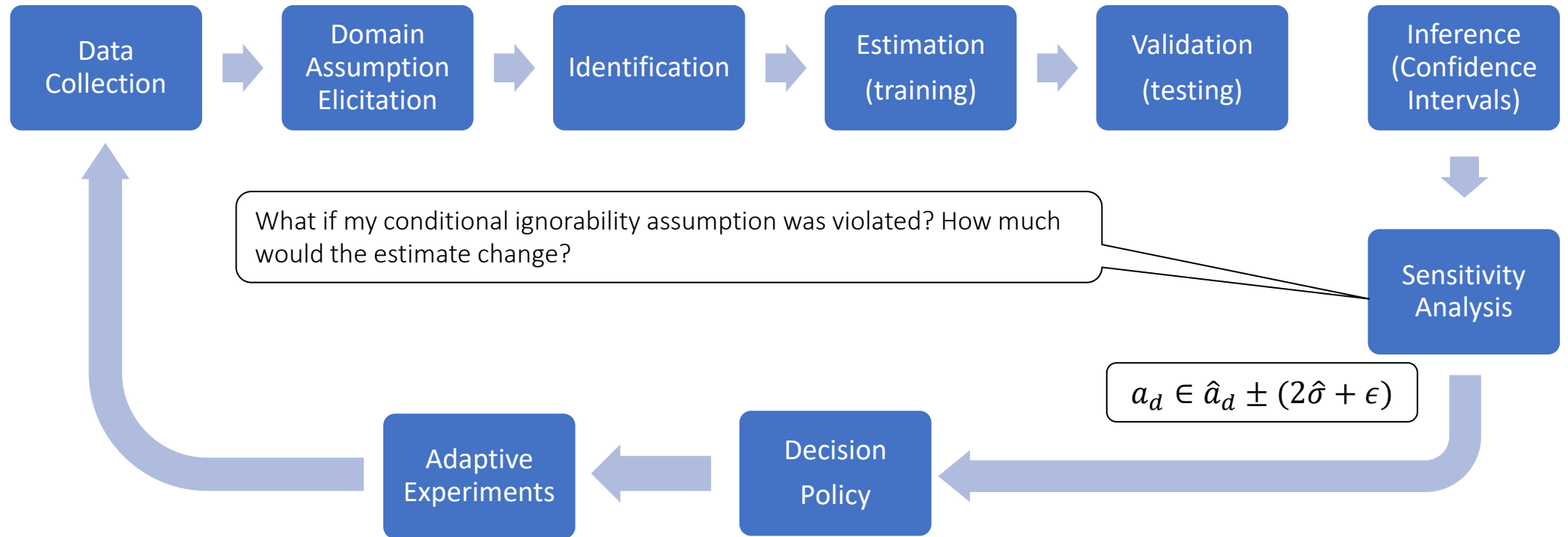


# Causal Inference Pipeline

Theory

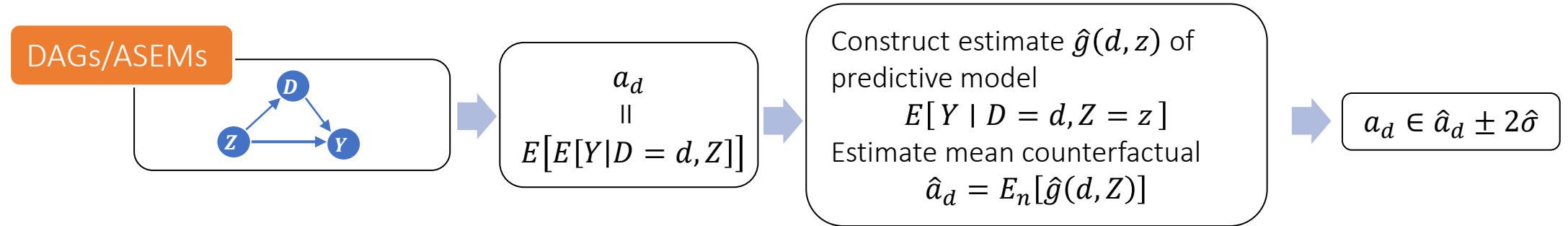


Practice

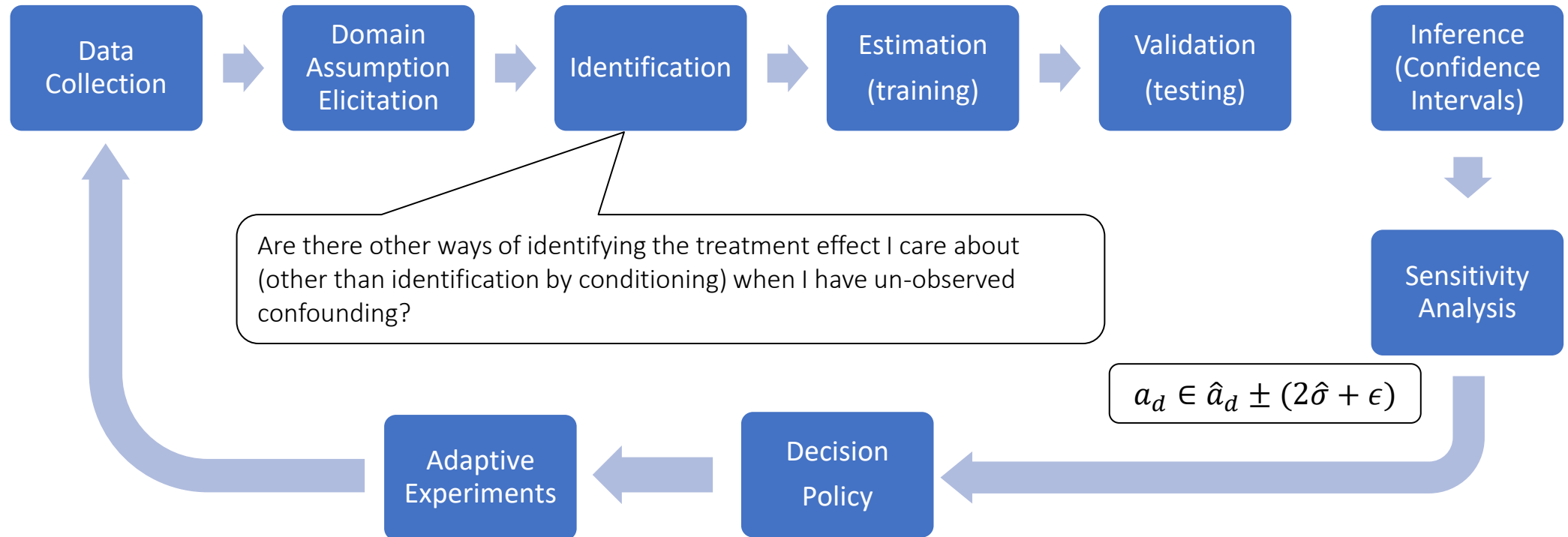


# Causal Inference Pipeline

Theory



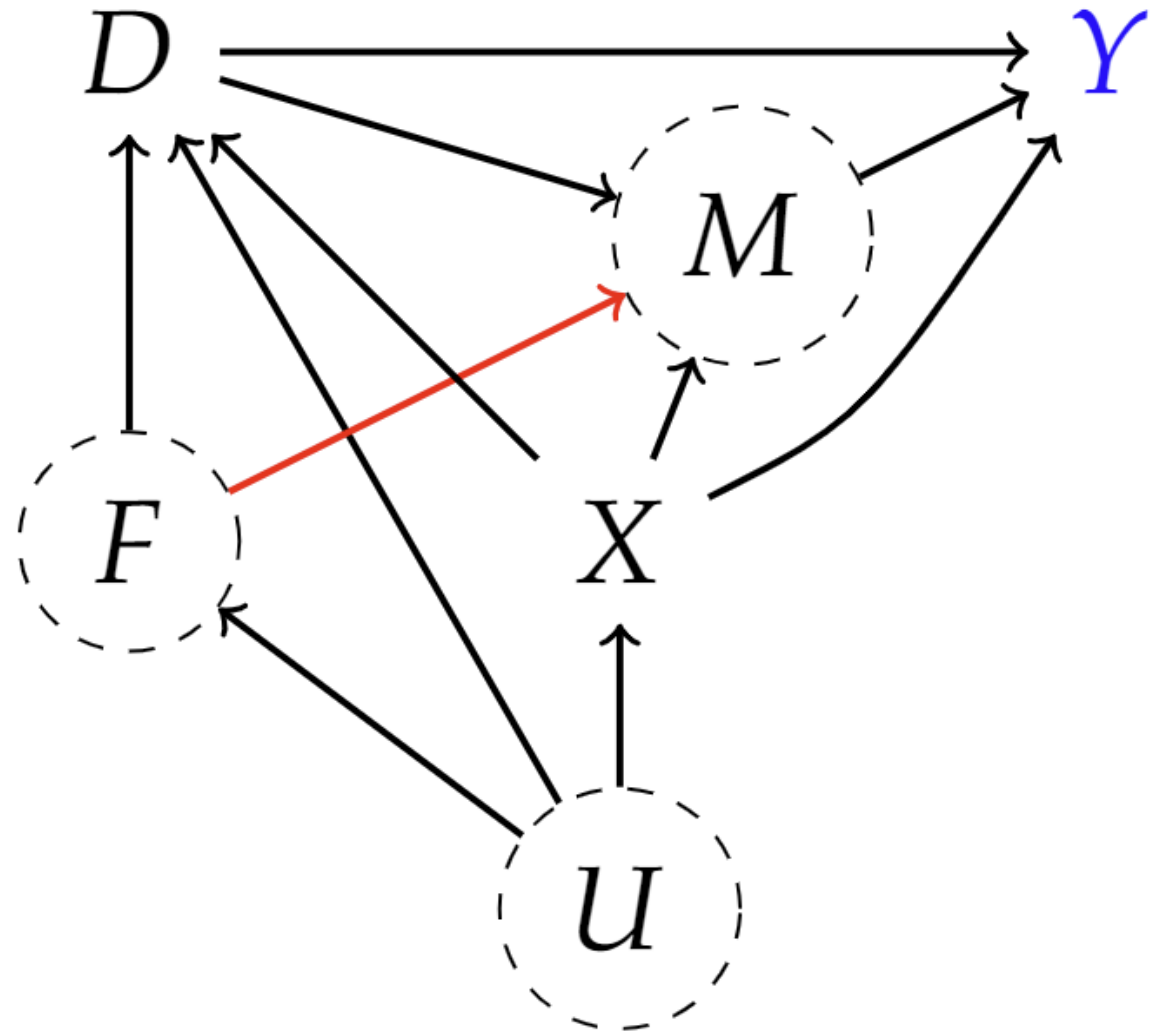
Practice



# Possible Violations

---

- F: firm characteristics
- D: eligibility for 401k
- Y: net financial assets
- X: age, income, family size, years of education, a married indicator, a two-earner status indicator, a defined benefit pension status indicator, an IRA participation indicator, and a home ownership indicator
- M: match amount

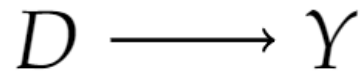




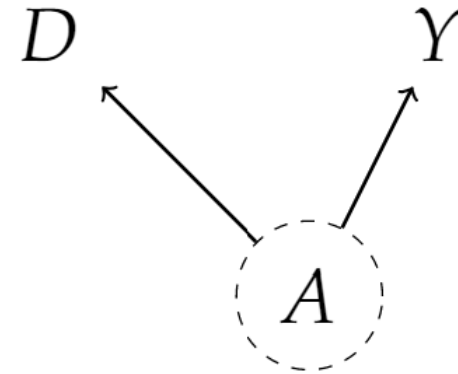
# Unobserved Confounding: Overview of Today's Content

# Unobserved Confounding

- If there are confounding factors that are un-observed, we cannot distinguish between an effect and a spurious correlation, without further structure



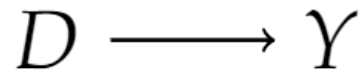
**Figure 4.1:**  $D$  causes  $Y$



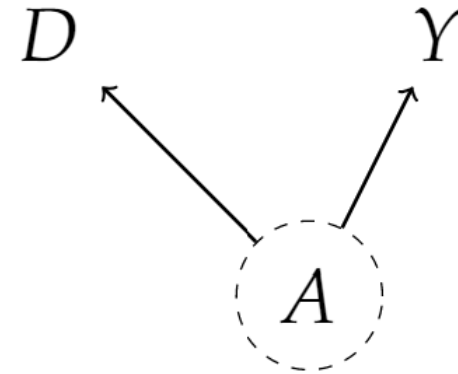
**Figure 4.2:**  $D$  and  $Y$  are caused by a latent factor  $A$

# Unobserved Confounding

- If there are confounding factors that are un-observed, we cannot distinguish between an effect and a spurious correlation, without further structure



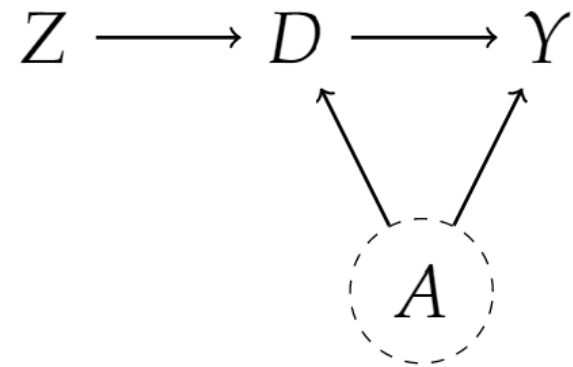
**Figure 4.1:**  $D$  causes  $Y$



**Figure 4.2:**  $D$  and  $Y$  are caused by a latent factor  $A$

# One Type of Structure: Instruments

- We already saw one example of more structure in the assignments (which one?)
- The structure we will investigate today are instruments



**Figure 4.3:** A DAG with Latent Confounder  $A$  and Instrument  $Z$ .

# Bias Bounds

# Very Frequently Unobserved Confounders

- Average treatment effect not “identifiable”

$$\theta_0 \neq E[E[Y|T = 1, X] - E[Y | T = 0, X]]$$

- Realistic conditional exogeneity

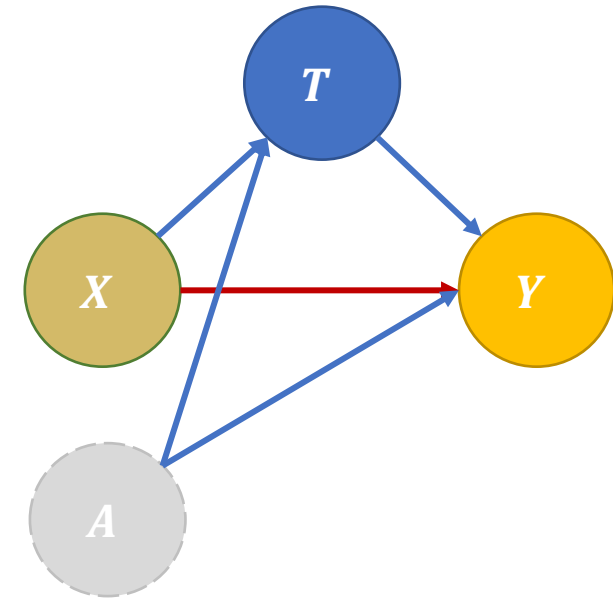
$$Y^{(d)} \perp T \mid X, A \quad (\text{conditional exogeneity})$$

- Ideal quantity: hypothetical g-formula

$$\theta_0 = E[E[Y|T = 1, X, A] - E[Y | T = 0, X, A]]$$

- Identifiable quantity:

$$\theta_s = E[E[Y|T = 1, X] - E[Y | T = 0, X]]$$



# Omitted Variable Bias

- We want to estimate:

$$\theta_0 := E[g(1, X, A) - g(0, X, A)]$$

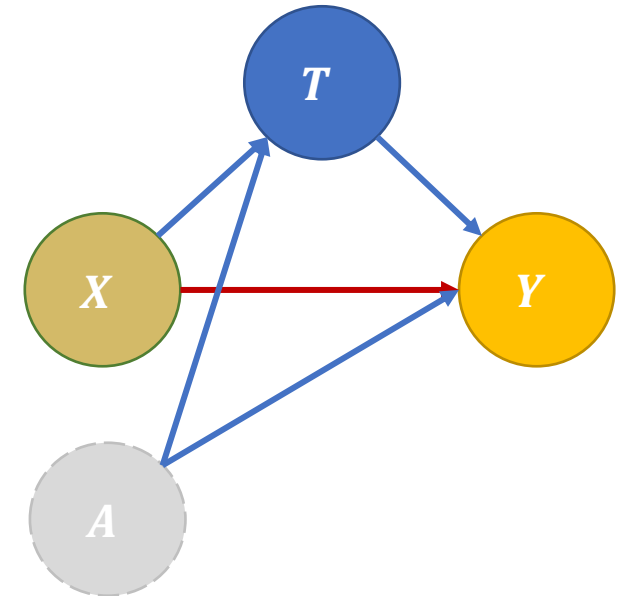
$$g(T, X, A) := E[Y | T, X, A]$$

- Which depends on an un-attainable “long regression”
- We can only estimate a “short regression”

$$g_s(T, X) := E[Y | T, X] = E[g(T, X, A) | T, X]$$

- And compute “short estimate”

$$\theta_s = E[g_s(1, X) - g_s(0, X)]$$



# Omitted Variable Bias Bounds

- Provide expression and construct bounds on Omitted Variable Bias (OMVB)

$$\theta_s - \theta_0$$

- Under interpretable assumptions that limit the strength of unobserved confounding
- Perform statistical inference on  $\theta_0$  allowing for ML regressions
- Sensitivity analysis has a long history:
  - Rosenbaum-Rubin'83: non-parametric bounds [non-sharp]
  - A lot of follow-up work making parametric assumptions



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# Omitted Variable Bias: Partially Linear Models

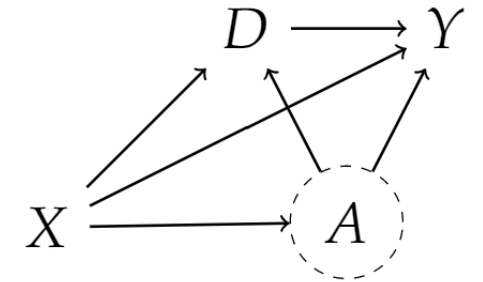
- Let's consider a simpler structural equation model

$$Y := aD + \delta A + f_Y(X) + \epsilon_Y$$

$$D := \gamma A + f_D(X) + \epsilon_D$$

$$A := f_A(X) + \epsilon_A$$

$$X := \epsilon_X$$



**Figure 4.5:**  $X$  are observed confounders, and  $A$  are unobserved confounders.

# Omitted Variable Bias: Partially Linear Models

- Suppose we run the residual-on-residual process and first partial out  $X$
- For convenience  $E[\epsilon_A^2] = 1$

$$\tilde{Y} := a\tilde{D} + \delta\tilde{A} + \epsilon_Y$$

$$\tilde{D} := \gamma\tilde{A} + \epsilon_D$$

$$\tilde{A} := \epsilon_A$$

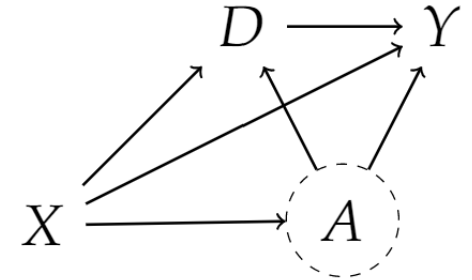


Figure 4.5:  $X$  are observed confounders, and  $A$  are unobserved confounders.

- Then the double ML method would run OLS of  $\tilde{Y}$  on  $\tilde{D}$

$$\theta_s = \frac{E[\tilde{Y}\tilde{D}]}{E[\tilde{D}^2]} = \frac{E[a\tilde{D}^2 + \delta\tilde{A}\tilde{D}]}{E[\tilde{D}^2]} = a + \delta \frac{E[\gamma\tilde{A}^2]}{E[\tilde{D}^2]} = a + \frac{\delta\gamma}{\gamma^2 + E[\epsilon_D^2]}$$

# Bias Bounds

- If the analyst can provide bounds on the strength of each relationship (e.g.  $\delta$ ,  $\gamma$ ,  $E[\epsilon_D^2]$ ) then we can provide bounds on the true effect

$$\theta_0 = \theta_s \pm \left| \frac{\delta\gamma}{\gamma^2 + E[\epsilon_D^2]} \right|$$

Measurable from the data

- More interpretable bounds:

$$\left( \frac{\delta\gamma}{\gamma^2 + E[\epsilon_D^2]} \right)^2 = R_{\tilde{Y} \sim \tilde{A} | \tilde{D}}^2 \frac{R_{\tilde{D} \sim \tilde{A}}^2}{1 - R_{\tilde{D} \sim \tilde{A}}^2} \frac{E[(\tilde{Y} - \theta_s \tilde{D})^2]}{E[\tilde{D}^2]}$$

$R^2$  in linear regression of  $\tilde{Y}$  on  $\tilde{A}$  after linearly partialling out  $\tilde{D}$

$R^2$  in linear regression of  $\tilde{D}$  on  $\tilde{A}$



# Bias Bounds

- If the analyst can provide bounds on the strength of each relationship (e.g.  $\delta$ ,  $\gamma$ ,  $E[\epsilon_D^2]$ ) then we can provide bounds on the true effect

$$\theta_0 = \theta_s \pm \left| \frac{\delta\gamma}{\gamma^2 + E[\epsilon_D^2]} \right|$$

Measurable from the data

- More interpretable bounds:

$$\left( \frac{\delta\gamma}{\gamma^2 + E[\epsilon_D^2]} \right)^2 = R_{Y \sim A|D,X}^2 \frac{R_{D \sim A|X}^2}{1 - R_{D \sim A|X}^2} \frac{E[(\tilde{Y} - \theta_s \tilde{D})^2]}{E[\tilde{D}^2]}$$

For more details:

[Making Sense of Sensitivity: Extending Omitted Variable Bias](#)

For more general analysis see:

[Long Story Short: Omitted Variable Bias in Causal Machine Learning](#)

Reduction in unexplained variance of  $Y$  when adding  $A$  in the model that predicts  $Y$  from treatment and controls

Reduction in unexplained variance of  $D$  when adding  $A$  in the model that predicts  $D$  from controls

# Bias Bounds

- The analyst provides bounds on the partial  $R^2$

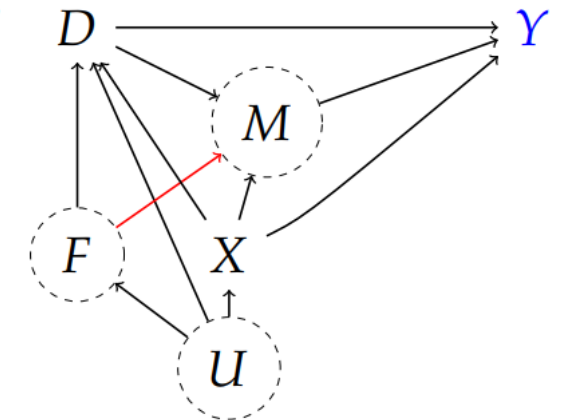
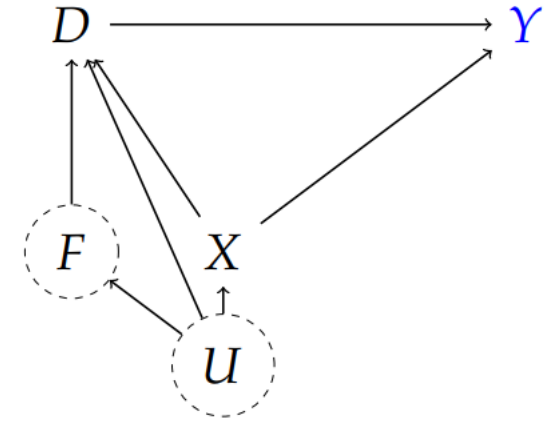
$$R_{Y \sim A|D,X}^2 \leq C_Y^2, \quad R_{D \sim A|X}^2 \leq C_D^2$$

- Based on these bounds we can conclude that

$$\theta_0 \in \theta_s \pm \sqrt{C_Y^2 \frac{C_D^2}{1 - C_D} \frac{E[(\tilde{Y} - \theta_s \tilde{D})^2]}{E[\tilde{D}^2]}}$$

# Application: 401k eligibility

- $Y$ =net financial assets
- $D$ =eligibility to enroll in 401(k) program
- $X$ =pre-treatment worker-level covariates (observed)
- $F$ =pre-treatment firm-level covariates (unobserved)
- $M$ =amount of contribution matched by employer
- $U$ =general latent factors



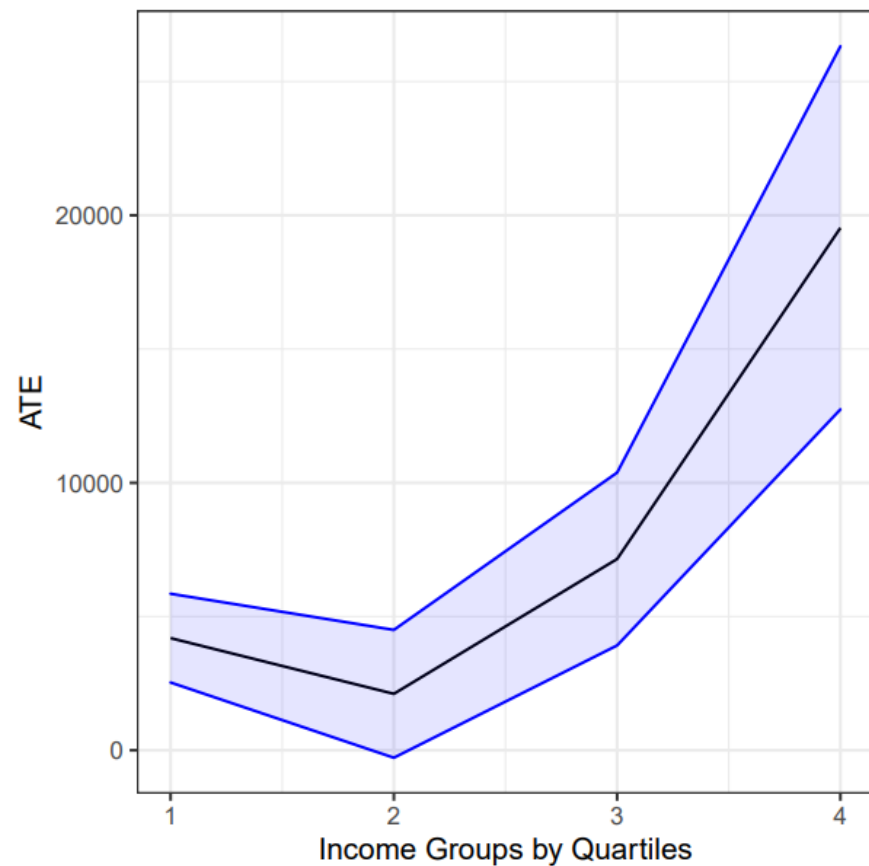
Controlling for  $X$  is sufficient in top figure but not bottom

# Confounding Scenario

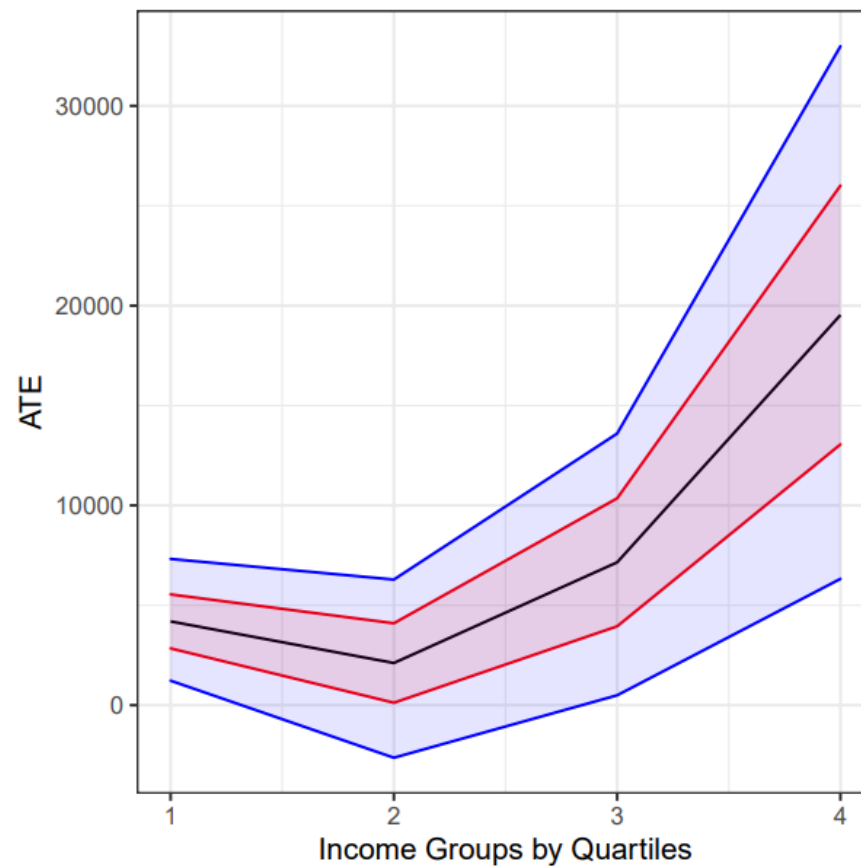
- Posit that  $F$  explains as much variation in net financial assets as the total variation of maximal matched percentage (5%) of income over period of three years
- Posit that  $F$  explains an additional 2.5% of the variation in 401k eligibility, a 20% relative increase in the baseline  $R^2$  of the treatment of 13%
- In PLR: translates to  $C_Y^2 := R_{Y \sim A|D,X}^2 \approx 4\%$ ,  $C_D^2 := R_{D \sim A|X}^2 \approx 3\%$

**Robustness value (RV)** = minimal equal strength of  $C_Y^2$  and  $C_D^2$  s.t. bound includes zero

- RV=5.5% (at 95% significance level) > 4%,3%
- Finding that 401k eligibility has positive effect is robust to this confounding scenario

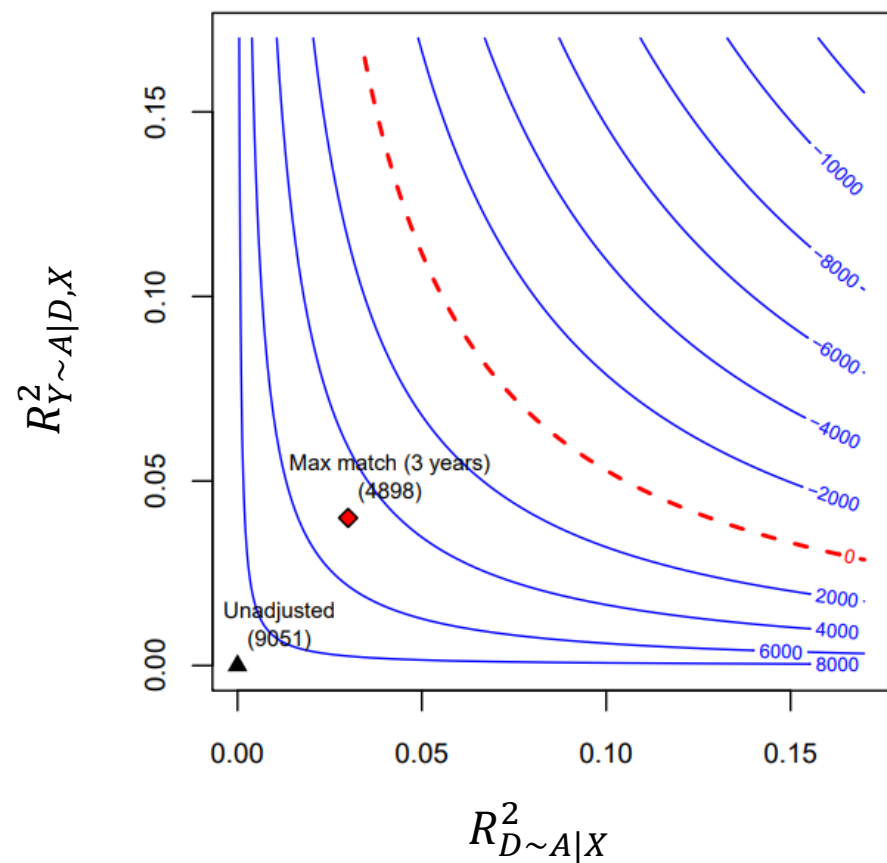


**(a)** Estimates under no confounding.

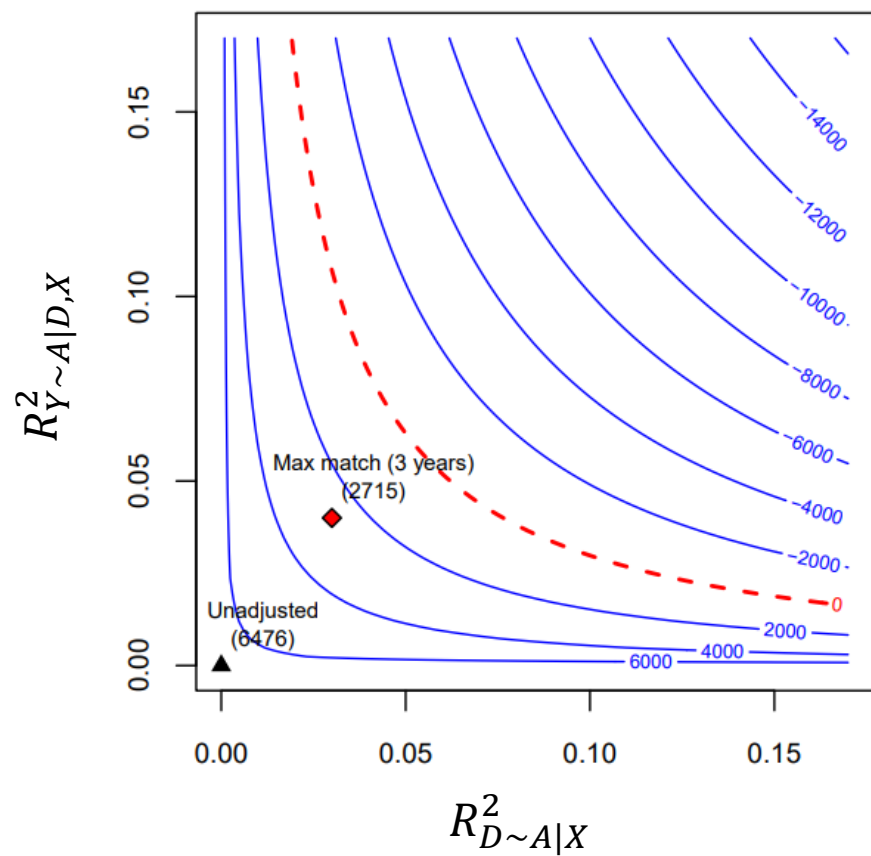


**(b)** Bounds under posited confounding.

**Note:** Estimate (black), bounds (red), and confidence bounds (blue) for the ATE. Confounding scenario:  $\rho^2 = 1$ ;  $C_Y^2 \approx 0.04$ ;  $C_D^2 \approx 0.031$ . Significance level of 5%.



(a) Contours for  $\theta_- = \theta_s - |B|$ .

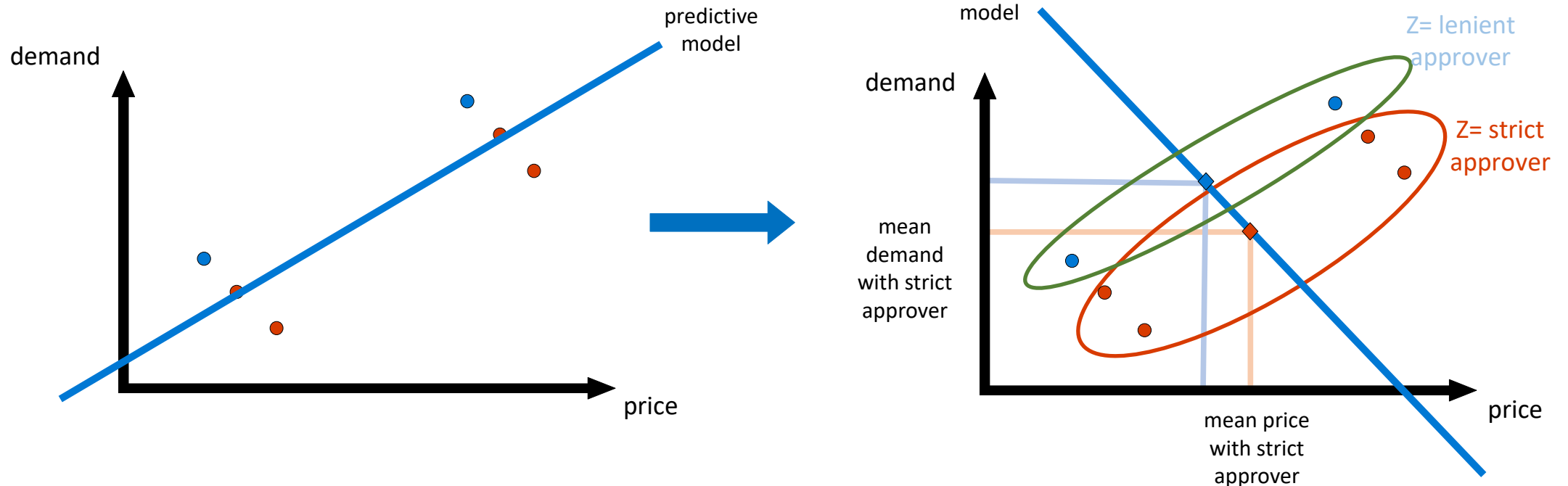
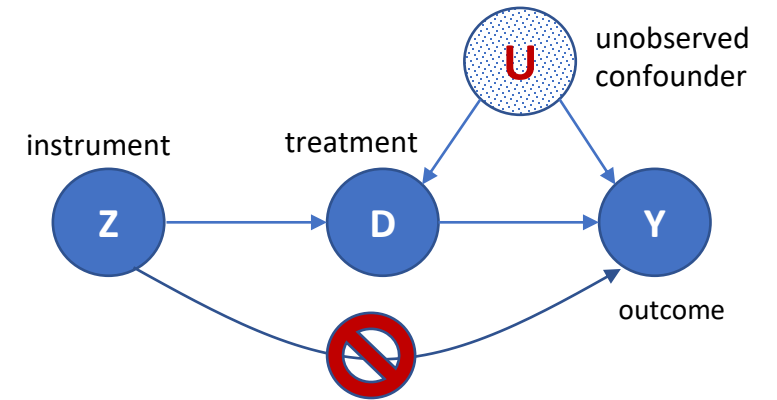


(b) Contours lower limit confidence bound.

Can we recover the true effect?  
Instrumental Variables

# Instrumental Variables and 2SLS

**Instrumental Variable:** any random variable  $Z$  that affects the treatment (log-price)  $D$  but does not affect the outcome (log-demand)  $Y$  other than through the treatment [Wright'28, Bowden-Turkington'90, Angrist-Krueger'91, Imbens-Angrist'94]

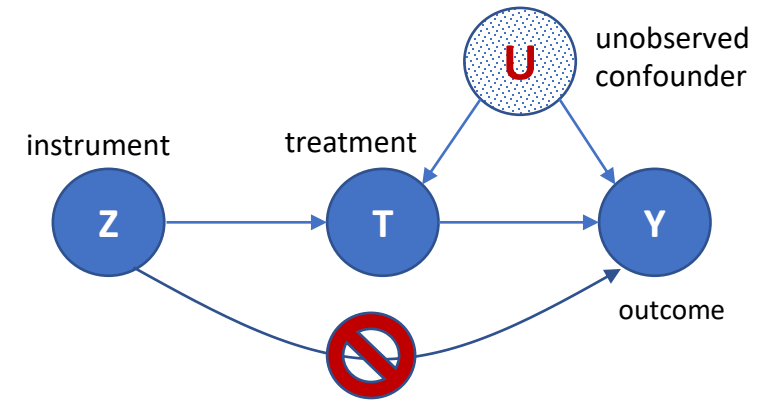




# Instrumental Variables and 2SLS

Instruments are widely used

- In the discount example (see also [Kling AER06] for effects of incarceration)
  - Discounts are sent to an approver desk
  - Approver assignment is random and different approvers are more or less “lenient”
  - Approver leniency is an instrument
- In healthcare [Doyle et al., JPE15]
  - Random assignment to ambulance companies of nearby patients is an instrument for measuring hospital quality
- In Tech [S., NeurIPS19]
  - Recommendation A/B tests as instruments for the effects of downstream actions



# Identification of Causal Effects via Instruments

**Phillip Wright's idea (1928):** the first causal path diagram analysis

- ◆ We can estimate effect of  $Z$  on  $y$  via a regression

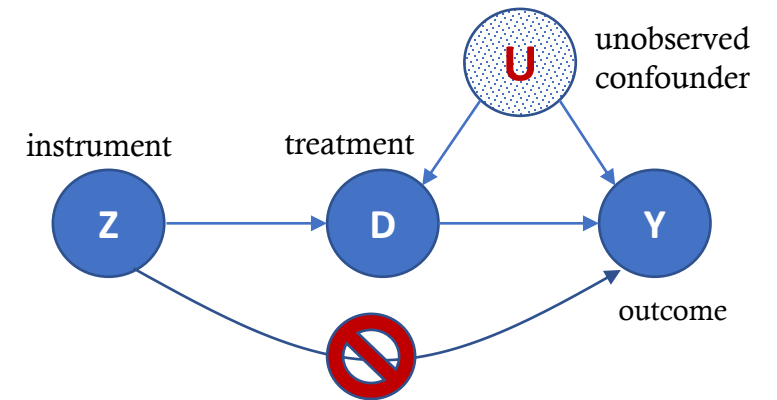
$$\gamma = \frac{\mathbb{E}[\tilde{Z}\tilde{y}]}{\mathbb{E}[\tilde{Z}^2]}$$

- ◆ We can estimate the effect of  $Z$  on  $D$  via a regression

$$\delta = \frac{\mathbb{E}[\tilde{Z}\tilde{D}]}{\mathbb{E}[\tilde{Z}^2]}$$

- ◆ The effect of  $Z$  on  $Y$  ( $\gamma$ ) is the product of the effect of  $Z$  on  $T$  ( $\delta$ ) multiplied by the effect of  $T$  on  $y$  ( $\theta$ )

$$\theta = \frac{\gamma}{\delta} = \frac{\mathbb{E}[\tilde{Z}\tilde{y}]}{\mathbb{E}[\tilde{Z}\tilde{D}]}$$



# Partially Linear Instrumental Variable Model

- Typically for continuous treatment/instrument a partially linear structural equation assumed

$$\begin{aligned}Y &:= \theta_0 D + f_Y(X) + A + \epsilon_Y \\D &:= \beta Z + f_D(X) + \beta A + \epsilon_D \\Z &:= f_Z(X) + \epsilon_Z \\A &:= f_A(X) + \epsilon_A\end{aligned}$$

All errors are exogenous and un-correlated

# Partially Linear Instrumental Variable Model

- After partialling out the observed controls  $X$

$$\begin{aligned}\tilde{Y} &:= \theta_0 \tilde{D} + \tilde{A} + \epsilon_Y \\ \tilde{D} &:= \beta \tilde{Z} + \beta \tilde{A} + \epsilon_D \\ \tilde{Z} &:= \epsilon_Z \\ \tilde{A} &:= \epsilon_A\end{aligned}$$

- We see immediately that:

$$\tilde{Y} := \theta_0 \tilde{D} + U, \quad U := \tilde{A} + \epsilon_Y \perp \tilde{Z}$$

- Since  $\epsilon_A, \epsilon_Y, \epsilon_Z$  are un-correlated:  $E[(\tilde{A} + \epsilon_Y)\tilde{Z}] = 0$
- Thus we have the moment restriction:  $E[(\tilde{Y} - \theta_0 \tilde{D})\tilde{Z}] = 0$

# Partially Linear Instrumental Variable Model

- After partialling out the observed controls  $X$

$$\begin{aligned}\tilde{Y} &:= \theta_0 \tilde{D} + \tilde{A} + \epsilon_Y \\ \tilde{D} &:= \beta \tilde{Z} + \beta \tilde{A} + \epsilon_D \\ \tilde{Z} &:= \epsilon_Z \\ \tilde{A} &:= \epsilon_A\end{aligned}$$

- Thus we have the moment restriction:  $E[(\tilde{Y} - \theta_0 \tilde{D})\tilde{Z}] = 0$
- We re-derive a generalization of Wright's formula

$$\theta_0 = \frac{E[\tilde{Y}\tilde{Z}]}{E[\tilde{D}\tilde{Z}]}$$

# Partially Linear Instrumental Variable Model

- After partialling out the observed controls  $X$

$$\begin{aligned}\tilde{Y} &:= \theta_0 \tilde{D} + \tilde{A} + \epsilon_Y \\ \tilde{D} &:= \beta \tilde{Z} + \beta \tilde{A} + \epsilon_D \\ \tilde{Z} &:= \epsilon_Z \\ \tilde{A} &:= \epsilon_A\end{aligned}$$

- Setting falls into the general moment estimation framework

$$M(\theta, h, p, m) = E \left[ \left( Y - h(X) - \theta (D - p(X)) \right) (Z - m(X)) \right] = 0$$

- Where  $h(X) = E[Y|X]$ ,  $p(X) = E[D|X]$ ,  $m(Z) = E[Z|X]$

# Orthogonal Method: Double ML for IV

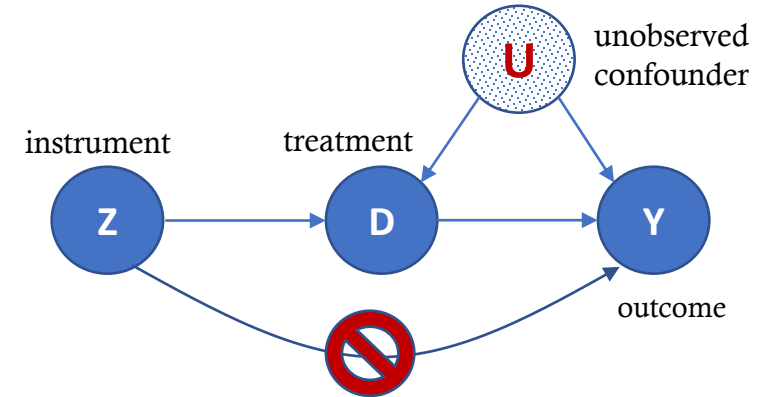
**Double ML.** Split samples in half

- Regress  $Y \sim X$  with ML on first half, to get estimate  $\hat{h}(S)$  of  $E[Y|X]$
- Regress  $D \sim X$  with ML on first half, to get estimate  $\hat{p}(S)$  of  $E[D|X]$
- Regress  $Z \sim X$  with ML on first half, to get estimate  $\hat{m}(S)$  of  $E[Z|X]$
- Construct residuals on other half,  $\hat{Z} = Z - \hat{m}(X)$ ,  $\hat{D} := D - \hat{p}(X)$  and  $\hat{Y} := Y - \hat{h}(X)$
- Solve moment condition:

$$E_n[(\hat{Y} - \theta \hat{D})\hat{D}] = 0$$

```
from econml.iv.dml import OrthoIV
orthoiv = OrthoIV()
orthoiv.fit(y, D, Z, W=X).effect_inference()
```

# The Binary Case



**Imbens-Angrist (1994):** core contribution of Nobel 2022 award

- Instrument/Treatment are binary (instrument=recommended treatment)
- Assume monotonicity:  $D^{(1)} \geq D^{(0)}$
- Recommended treatment cannot reverse taken treatment
- Object of interest: Local Average Treatment Effect (ATE among compliers)

$$\theta_0 = E[Y^{(1)} - Y^{(0)} | D^{(1)} > D^{(0)}]$$

- Proof [Angrist-Imbens'94]:

$$\theta_0 = \frac{E[(Y^{(1)} - Y^{(0)})1\{D^{(1)} > D^{(0)}\}]}{E[1\{D^{(1)} > D^{(0)}\}]} = \frac{E[Y^{(D^{(1)})} - Y^{(D^{(0)})}]}{E[D^{(1)} - D^{(0)}]} = \frac{ATE(Z \rightarrow Y)}{ATE(Z \rightarrow D)}$$

$\gamma = \frac{E[\tilde{Z}\tilde{y}]}{E[\tilde{Z}^2]}$

$\delta = \frac{E[\tilde{Z}\tilde{D}]}{E[\tilde{Z}^2]}$



# The Binary Case

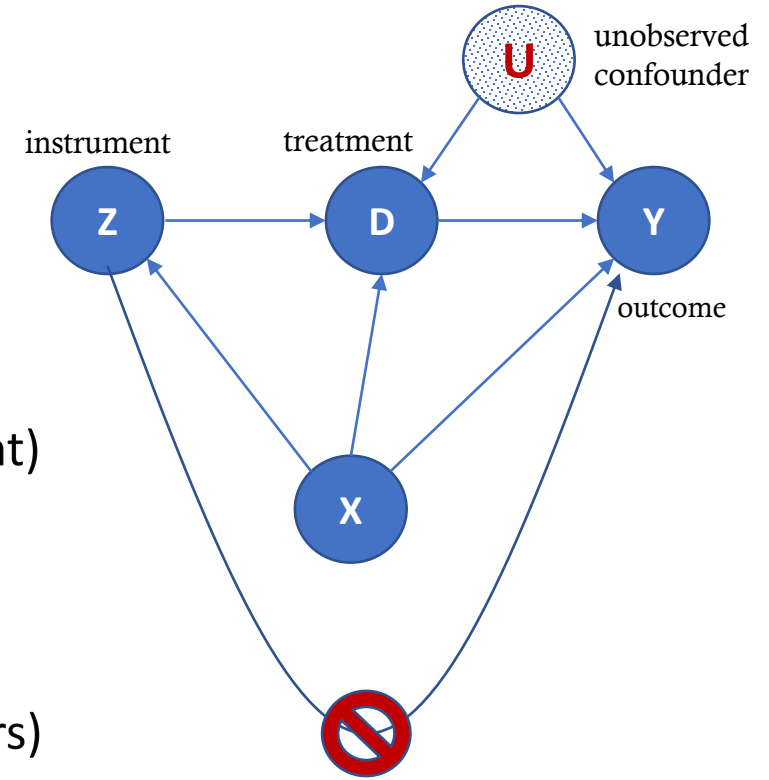
**Imbens-Angrist (1994):** core contribution of Nobel 2022 award

- Instrument/Treatment are binary (instrument=treatment)
- Assume monotonicity:  $D^{(1)} \geq D^{(0)}$
- Recommended treatment cannot reverse taken treatment
- Object of interest: Local Average Treatment Effect (ATE among compliers)

$$\theta_0 = E[Y^{(1)} - Y^{(0)} | D^{(1)} > D^{(0)}]$$

- Proof [Angrist-Imbens'94]:

$$\theta_0 = \frac{E[(Y^{(1)} - Y^{(0)})1\{D^{(1)} > D^{(0)}\}]}{E[1\{D^{(1)} > D^{(0)}\}]} = \frac{E[Y^{(D(1))} - Y^{(D(0))}]}{E[D^{(1)} - D^{(0)}]} = \frac{ATE(Z \rightarrow Y)}{ATE(Z \rightarrow D)}$$



$$E[E[Y|Z = 1, X] - E[Y|Z = 0, X]]$$

ATE(Z → Y)

ATE(Z → D)

$$E[E[D|Z = 1, X] - E[D|Z = 0, X]]$$

# LATE in the Binary Case

- Under monotonicity

$$\theta_0 = \frac{E[E[Y | Z = 1, X] - E[Y | Z = 0, X]]}{E[E[D | Z = 1, X] - E[D | Z = 0, X]]}$$

- Moment formulation

$$E[E[Y | Z = 1, X] - E[Y | Z = 0, X] - \theta_0(E[D | Z = 1, X] - E[D | Z = 0, X])] = 0$$

$$+ a_{Z \rightarrow Y}(Z, X)(Y - E[Y | Z, X]) + a_{Z \rightarrow D}(Z, X)(D - E[D | Z, X])$$

- Orthogonal moment formulation: apply ATE debiasing twice