

Structural Causal Models & Instrumental Variable

Group 22:

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Summary

Motivation

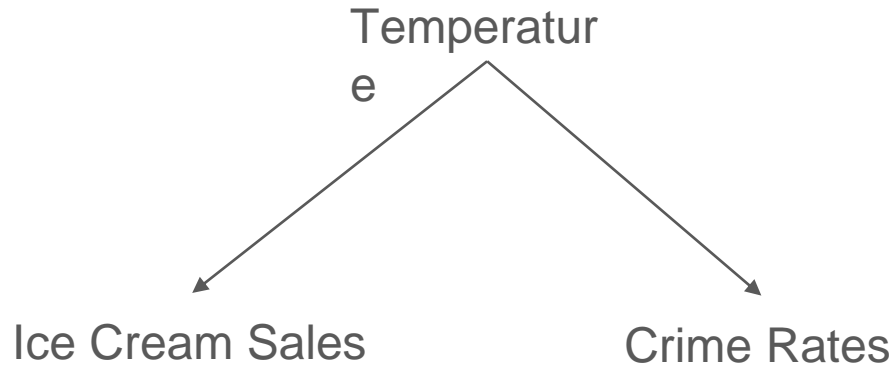
Regression VS Causation

Structural Causal Model Theory by Judea Pearl

Final Project: Instrumental Variable

Motivation - Omitted Variables

An increase in ice cream sales is correlated with an increase in violent crime—not because ice cream causes crime, but because both ice cream sales and violent crime are more common in hot weather.



Problems of Correlation (Endogeneity)

Errors in Variables (lie in the surveys)

Reverse Causality (ability = $a * \text{income}$)

Simultaneity (e.g. Supply and Demand)

Omitted Variables (ice cream sales & crime rate)



CAUSAL INFERENCE IN STATISTICS

A Primer

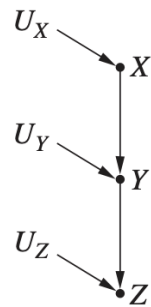
Judea Pearl
Madelyn Glymour
Nicholas P. Jewell

WILEY

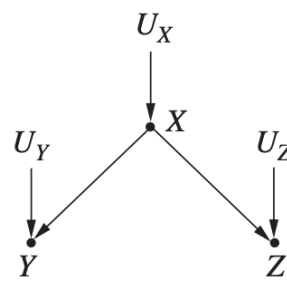


Graphical Causal Models Theories

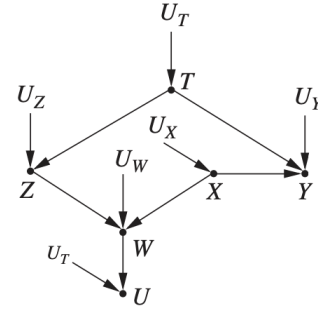
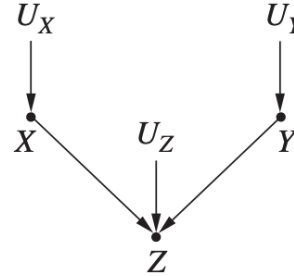
Chain



Fork



Collider



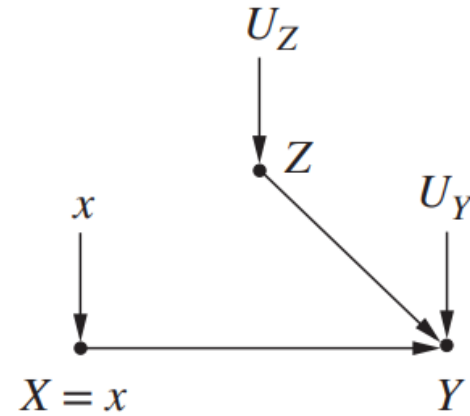
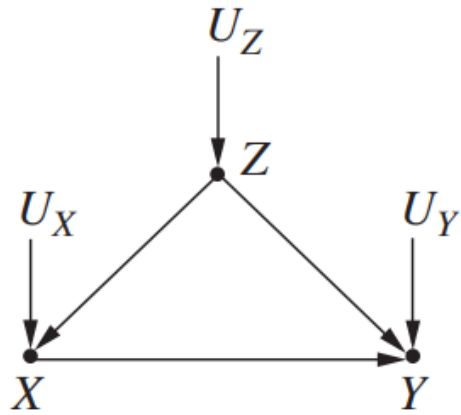
Endogenous and Exogenous Variable

Independence and Conditional Independence

d-connected and d-separated

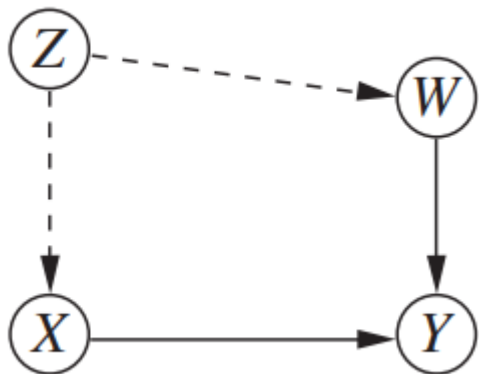
Intervene

$Y=y \mid \text{do}(X=x)$



Causal Effect = $E(Y \mid \text{do}(X = x+1)) - E(Y \mid \text{do}(X = x))$

Back-Door Criterion



$$P(Y = y \mid do(X = x)) = \sum_z P(Y = y \mid X = x, Z = z)P(Z = z)$$

Conditional on Z

1. We block all spurious paths between X and Y.
2. We leave all directed paths from X to Y unperturbed.
3. We create no new spurious paths

Direct Effect in Linear Situation

Assumption: the relationships between variables are linear, and that all error terms have Gaussian distributions. X and all Z are the causal factors

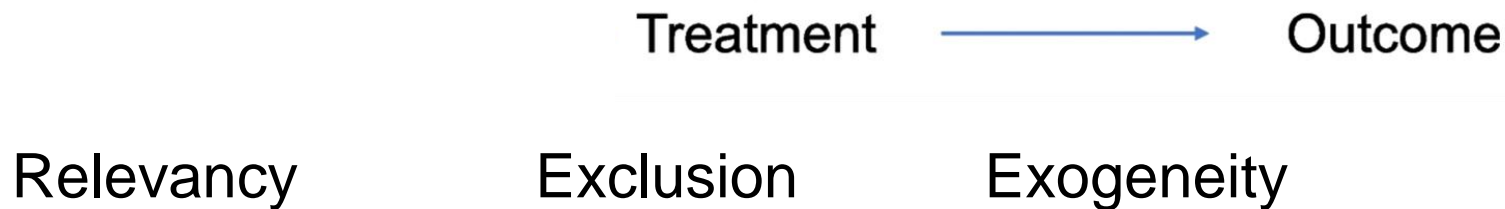
$$Y = aX + \beta_1 Z_1 + \beta_2 Z_2 + \dots + \varepsilon \quad \varepsilon \sim G(0,1)$$

under backdoor criteria

Causal Effect = a

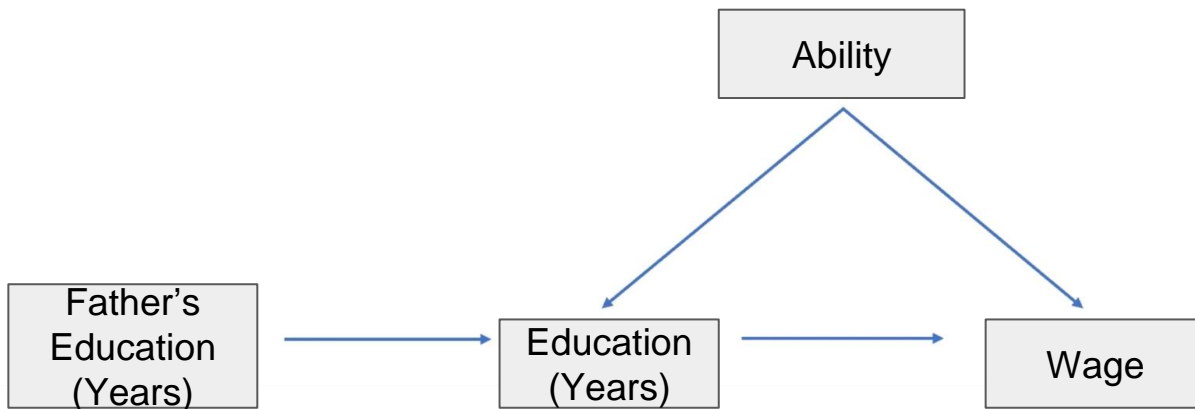
Instrumental Variable

Instrument = “Tool”



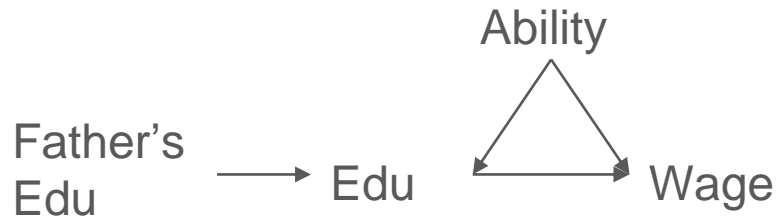
Project: Does an extra Year of Education causes Increased Wages

Instrumental Variable Method

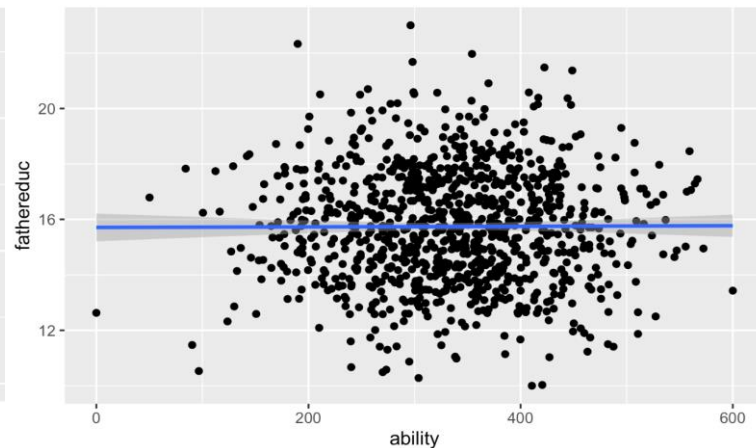
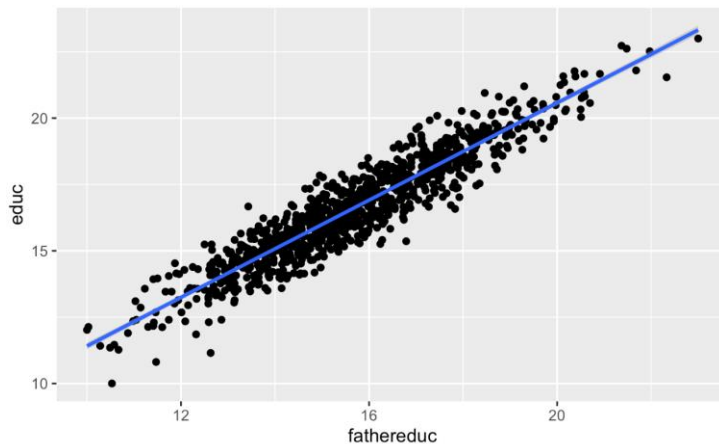


Does an extra Year of Education causes Increased Wages?

Part 2: Instrumental Variable Assumptions

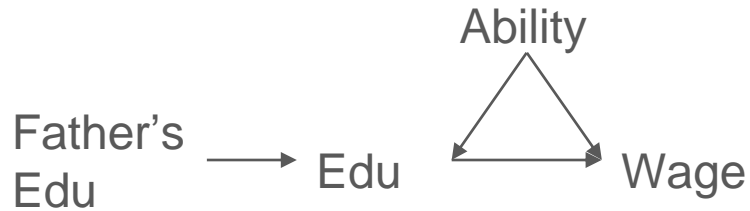


Relevancy, Exclusion, Exogeneity



Does an extra Year of Education causes Increased Wages?

Part 1: Explore the use of Instrumental Variable



Interested in how **Edu** influences **Wage**
Ability as confounder
Father's Edu as Instrumental Variable

Methodology:

Fake Data -> **Ability** is accessible
Regress **Wage** with **Edu** & **Ability**

$$\text{Wage} = \alpha \text{Edu} + \beta \text{Ability} + \varepsilon \rightarrow \text{reveal true } \alpha$$

Regress **Edu** with **Father's Edu**

$$\text{Edu} = a(\text{Father's Edu}) + \varepsilon$$

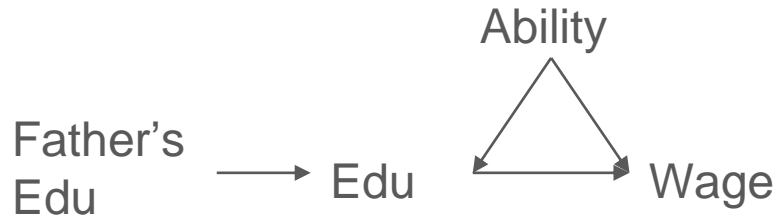
Obtain **Edu_hat**

Regress **Wage** with **Edu_hat**

$\text{Wage} = \alpha \text{Edu_hat} + \varepsilon$ -> Theoretically
same α

Does an extra Year of Education causes Increased Wages?

Part 3: Computations



Regress **Wage** with **Edu & Ability**

$$\text{Wage} = \alpha \text{Edu} + \beta \text{Ability} + \varepsilon \quad \alpha = 7.767$$

Regress **Edu** with **Father's Edu**

$$\text{Edu} = a(\text{Father's Edu}) + \varepsilon$$

Regress **Wage** with **Edu_hat**

$$\text{Wage} = \alpha \text{Edu_hat} + \varepsilon \quad \alpha = 7.835$$

Naive Model:

$$\text{Regress } \mathbf{Wage} \text{ with } \mathbf{Edu} \quad \alpha' = 13.1$$

Instrumental Variable Model:

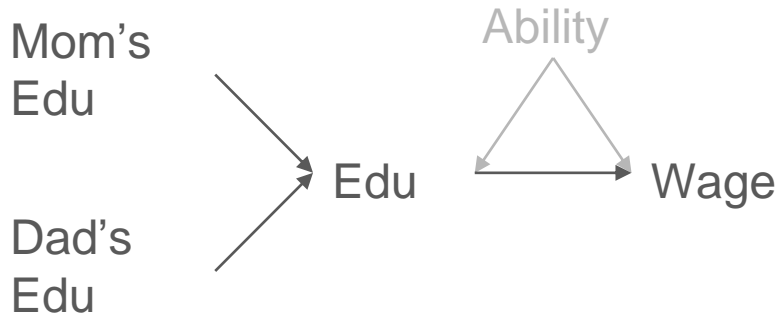
Regress **Edu** with **Father's Edu**

$$\text{Regress } \mathbf{Wage} \text{ with } \mathbf{Edu_hat} \quad \alpha = 7.835$$

Ready to explore real data without the need of Ability data!

Does an extra Year of Education causes Increased Wages?

Part 4: Real Data Analysis



Have both parents' Education as IVs to better predict children's Education
No longer have access to confounding variable Ability, but it still exists.
Regress **Edu** with **Mom's Edu** and **Dad's Edu**
Obtain **Edu_hat**
Regress **Wage** with **Edu_hat**
Coefficient is the desired α !

A year of education **causes** a 15.7% increase in annual wages, on average.

Data retrieved from paper <https://doi.org/10.3386/w3857>

Questions?

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