

Impact Evaluation in Firms and Organizations

With Applications in R and Python

Chapter 6: Instrumental Variables

6.1 Instruments and Complier Effects

6.2 Behavioral Assumptions and Methods

Limits of selection on observables

- The selection-on-observables assumption fails when treated and untreated subjects differ in unobserved characteristics that affect the outcome

Example

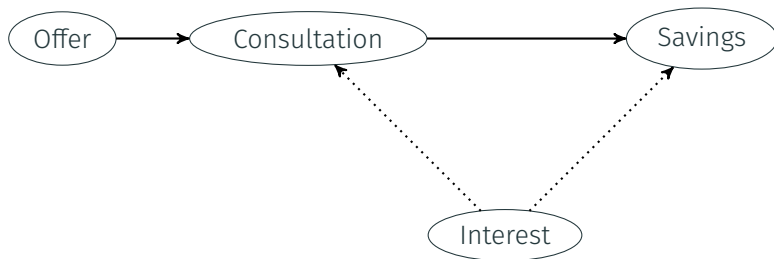
Imperfect compliance in an experimental setting

- Some customers offered financial consultation do not take it up
- Non-compliance may be driven by unobserved traits that influence both take-up and saving decisions
- Comparing recipients and non-recipients becomes misleading, as treated and control groups are no longer comparable

Conditions for recovering causal effects

- Impact evaluation may still be possible under additional behavioral assumptions
- **Assumption 1:** Exclusion restriction
 - Offer affects savings only through actual receipt of consultation
 - Violated if the offer alone increases attention to financial issues
- **Assumption 2:** Instrument independence
 - Offer must be independent of characteristics affecting savings
- **Assumption 3:** Compliance and weak monotonicity
 - The offer induces at least some customers to take up the intervention
 - Weak monotonicity assumption: The offer must not increase take-up for some customers while reducing it for others

Figure 6.1: A random offer as instrument for financial consultation



Role of key assumptions

- Random offer serves as an *instrument* for consultation receipt
- By the exclusion restriction and monotonicity assumption, the random offer affects the outcome only through its effect on intervention take-up among compliers

Estimating the effect among compliers

- Estimate average effect of the offer on the outcome
- Estimate average effect of the offer on intervention receipt
- Divide the outcome effect by the take-up effect
- This scaling accounts for the fact that only compliers contribute to the offer's effect on the outcome

Example of scaling argument

- Offer increases average savings by \$1,000
- Offer increases intervention receipt by 0.5 (i.e., 50% of customers are compliers)
- Effect among compliers equals $\$1,000 / 0.5 = \$2,000$

Local average treatment effect (LATE)

- Measures the intervention effect among compliers
- Effect is local because it applies only to the subgroup of compliers rather than the entire population

Example

LATE of customer loyalty program

- A company introduces a new customer loyalty program, offering exclusive discounts and rewards to members
- Loyalty program increases average spending by \$100
- Only 25% of customers (i.e., compliers) joined the program because of the offer
- LATE equals $\$100 / 0.25 = \400
- Implies that compliers increase spending by an average of \$400

6.1 Instruments and Complier Effects

6.2 Behavioral Assumptions and Methods

Instrument and potential variables

- Z denotes the random offer (instrument): $Z = 1$ if offered, $Z = 0$ otherwise
- $D(1)$ and $D(0)$ denote potential intervention states under $Z = 1$ and $Z = 0$
- $Y(1)$ and $Y(0)$ denote potential outcomes under $D = 1$ and $D = 0$

Behavioral assumptions

- Instrument validity assumption: $\{D(1), D(0), Y(1), Y(0)\} \perp Z$
- Weak monotonicity: $\Pr(D(1) \geq D(0)) = 100\%$
- Relevance condition: $E[D \mid Z = 1] - E[D \mid Z = 0] \neq 0$

$$\{D(1), D(0), Y(1), Y(0)\} \perp Z$$

Instrument validity assumption consists of two conditions:

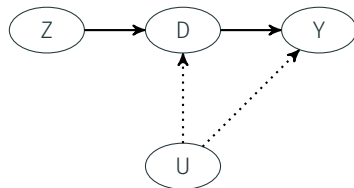
Independence condition

- Instrument Z must be independent of potential intervention and outcome states
- No characteristics may jointly affect Z and D or Y
- Random assignment of Z satisfies this condition

Exclusion restriction

- Instrument Z must not directly affect outcome Y
- Any effect of Z on Y must operate through intervention D

Figure 6.2: An instrumental variable approach



- Instrument independence holds: No unobserved characteristics jointly affect Z and Y
- Exclusion restriction holds: Z affects Y only through D

Monotonicity condition

$$Pr(D(1) \geq D(0)) = 100\%$$

- Instrument either increases intervention take-up ($D(1) > D(0)$) or has no effect on it ($D(1) = D(0)$)
- Instrument cannot decrease the take-up
- Automatically holds if intervention is inaccessible without the instrument

Instrument relevance

$$E[D \mid Z = 1] - E[D \mid Z = 0] \neq 0$$

- Implies the instrument affects intervention take-up
- Corresponds to the share of compliers when D is binary

Local average treatment effect (LATE)

- The assumptions on the previous slides identify the LATE for compliers
- LATE is formally defined as the difference in expected outcomes with intervention versus no intervention for compliers

$$\Delta_{D(1)=1, D(0)=0} = E[Y(1) - Y(0) \mid D(1) = 1, D(0) = 0] \quad (6.2)$$

Intention-to-treat (ITT) or reduced form effect

- $E[Y | Z = 1] - E[Y | Z = 0]$
- Measures the impact of the instrument on the outcome

First-stage effect

- $E[D | Z = 1] - E[D | Z = 0]$
- Measures the impact of the instrument on intervention take-up

Wald estimand

- Ratio of the reduced form effect to the first-stage effect:

$$\Delta_{D(1)=1, D(0)=0} = \frac{E[Y | Z = 1] - E[Y | Z = 0]}{E[D | Z = 1] - E[D | Z = 0]} \quad (6.3)$$

Two-stage regression

- Provides an alternative way to estimate the LATE
- Numerically equivalent to the Wald ratio

Structure of the two-stage approach

- First stage: regress intervention D on a constant and instrument Z
- Second stage: regress outcome Y on a constant and the predicted intervention from the first stage (i.e., $E[D | Z]$)

Need for conditional assumptions

- Instrument validity may fail unconditionally
- Groups with $Z = 1$ and $Z = 0$ may differ in observed covariates X
- If these covariates also affect the outcome, comparing $Z = 1$ and $Z = 0$ amounts to comparing apples with oranges

Example

Nonrandom assignment of offers

- Bank targets female customers more frequently
- Probability of receiving an offer depends on gender
- Instrument is not random with respect to gender

Conditional Instrumental Variable Assumptions

Controlling for covariates

- Instrument validity must hold conditional on X
- Behavioral assumptions are modified accordingly

Conditional instrumental variable assumptions

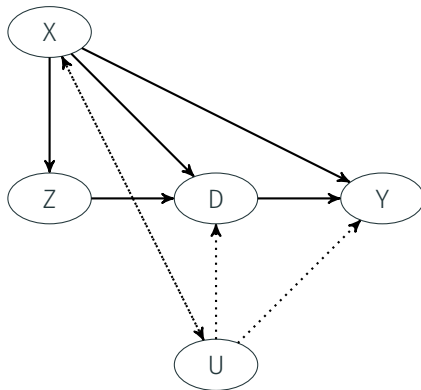
- $\{D(1), D(0), Y(1), Y(0)\} \perp Z \mid X$
- $\Pr(D(1) \geq D(0) \mid X) = 100\%$, $E[D \mid Z = 1, X] - E[D \mid Z = 0, X] \neq 0$
- Common support: $0\% < \Pr(Z = 1 \mid X) < 100\%$

Interpretation of the framework

- Instrument validity holds conditional on X
- Unobserved factors may affect X or be affected by X
- Conditional on X , no unobserved factor jointly affects Z and Y

An Instrumental Variable Approach with Covariates

Figure 6.3: An instrumental variable approach with covariates



Instrument effects with covariates

- Independence given X can be viewed as selection on observables for Z rather than D
- Effects of Z on Y or D are estimated conditional on X
- Reduced-form and first-stage effects can also be expressed using the propensity score $\Pr(Z = 1 | X)$

Conditional LATE expression

$$\begin{aligned}\Delta_{D(1)=1, D(0)=0} &= \frac{E[E[Y | Z = 1, X] - E[Y | Z = 0, X]]}{E[E[D | Z = 1, X] - E[D | Z = 0, X]]} \\ &= \frac{E[Y \cdot Z / \Pr(Z = 1 | X) - Y \cdot (1 - Z) / (1 - \Pr(Z = 1 | X))]}{E[D \cdot Z / \Pr(Z = 1 | X) - D \cdot (1 - Z) / (1 - \Pr(Z = 1 | X))]} \end{aligned} \quad (6.5)$$

Variable selection

- Covariates X may be selected based on prior knowledge or learned from high-dimensional data

X selected by the analyst

- ITT effect and first-stage effect are estimated using methods such as matching, regression, IPW, or doubly robust methods
- LATE is then obtained by dividing the ITT estimate by the first-stage estimate

X selected using a data-driven approach

- Use double machine learning (DML) to estimate the ITT and first-stage effects and then estimate the LATE