

# Chapter 24. Instrumental Variables Analysis of Randomized Experiments with Two-Sided Noncompliance

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## Previous chapters...

- ▶ Unconfoundness of the treatment of interest is questionable
- ▶ With the existence of noncompliers (one-sided)
  - $(W_i)$  / confounded
  - Instrumental variable  $\rightarrow$  estimate "local" average effects for the subpopulation
- ▶ Completely randomized design and one assumption
  - Completely randomized  $\rightarrow (Z_i)$ , unconfoundness  $\rightarrow$  enable to estimate ITT.
  - Exclusion assumptions  $\rightarrow$  allow to estimate "local" average effects for the compliers

## 24.1 Introduction

- ▶ IV analyses for two-sided noncompliance in a randomized experiment.
- ▶ Completely randomized and two assumptions
  - Completely randomized  $\rightarrow (Z_i)$ , unconfoundness  $\rightarrow$  ITT.
  - Exclusion assumptions and monotonicity assumption  $\rightarrow$  allow to estimate "local" average effects for the subpopulation of compliers

## 24.2 The Angrist Draft Lottery Data

- ▶ **Serving in the military (veteran / non-veteran) → earning**
- ▶ Angrist(1990) exploits the implementation of the draft during the Vietnam War.
  - All men of a certain age were required to register for the draft.
  - Draft priority was assigned randomly based on the birth dates per birth year
- ▶ Possibility of the existence of complier
  - Medical test / minimum educational level
  - Low lottery number → decided to enter graduate school / move to Canada

# The Angrist Draft Lottery Data

**Table 24.1.** *Summary Statistics for the Angrist Draft Lottery Data*

	Non-Veterans ( $N_c = 6,675$ )				Veterans ( $N_t = 2,030$ )			
	Min	Max	Mean	(S.D.)	Min	Max	Mean	(S.D.)
Draft eligible	0	1	0.24	(0.43)	0	1	0.40	(0.49)
Yearly earnings (in \$1,000's)	0	62.8	11.8	(11.5)	0	50.7	11.7	(11.8)
Earnings positive	0	1	0.88	(0.32)	0	1	0.91	(0.29)
Year of birth	50	52	51.1	(0.8)	50	52	50.9	(0.8)

## 24.3 Compliance Status

- ▶ Compliance Status

- A function of the pair of potential responses  $(W_i(0), W_i(1))$

- ▶ Compliance types

- Denote compliance type by  $G_i$

$$G_i = g(W_i(0), W_i(1)) = \begin{cases} \text{nt (nevertaker)} & \text{if } W_i(0) = 0, W_i(1) = 0, \\ \text{co (complier)} & \text{if } W_i(0) = 0, W_i(1) = 1, \\ \text{df (defier)} & \text{if } W_i(0) = 1, W_i(1) = 0, \\ \text{at (alwaystaker)} & \text{if } W_i(0) = 1, W_i(1) = 1. \end{cases}$$

## Compliance Status-One-sided case

- ▶ We only observed the realized treatment status of  $W_i(0)$  or  $W_i(1)$
- ▶ One-sided
  - If  $Z_i = 1, W_i^{obs} = 0 \rightarrow (W_i(0), W_i(1)) = (0, 0)$  / nc
  - If  $Z_i = 1, W_i^{obs} = 1 \rightarrow (W_i(0), W_i(1)) = (0, 1)$  / co
  - If  $Z_i = 0, W_i^{obs} = 0 \rightarrow (W_i(0), W_i(1)) = (0, 0)$  or  $(0, 1)$  / co or nc
  - If  $Z_i = 0, W_i^{obs} = 1 \rightarrow (W_i(0), W_i(1)) = (1, 0)$  or  $(1, 1)$  / co or nc



## Compliance Status-One-sided case

### ▶ Two-sided

- If  $Z_i = 1, W_i^{obs} = 0 \rightarrow (W_i(0), W_i(1)) = (0, 0)$  or  $(1, 0)$  / nt or df
- If  $Z_i = 1, W_i^{obs} = 1 \rightarrow (W_i(0), W_i(1)) = (0, 1)$  or  $(1, 1)$  / df or at
- If  $Z_i = 0, W_i^{obs} = 0 \rightarrow (W_i(0), W_i(1)) = (0, 0)$  or  $(0, 1)$  / nt or co
- If  $Z_i = 0, W_i^{obs} = 1 \rightarrow (W_i(0), W_i(1)) = (1, 0)$  or  $(1, 1)$  / df or at

### ▶ That is why two-sided noncompliance case is more complicated.

- Need additional assumption to identify the causal effect
- Monotonicity  $\rightarrow$  No defier

## 24.4 Intention-To-Treat Effects

- ▶ Largely unchanged from the one-sided case
- ▶ Unit-level effect of 4 compliance types
  - 1 for co
  - 0 for nt and at
  - -1 for df
- ▶ Super-population average ITT

$$\text{ITT}_W = \mathbb{E}_{\text{sp}} [W_i(1) - W_i(0)] = \pi_{\text{co}} - \pi_{\text{df}}$$

- ▶ The ITT effect on the primary outcome

$$\text{ITT}_Y = \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0))]$$

## Random Assignment of $Z_i$

- ▶ **Assumption 24.1 (Super-Population Random Assignment)**

$$Z_i \perp (W_i(0), W_i(1), Y_i(0, 0), Y_i(0, 1), Y_i(1, 0), Y_i(1, 1))$$

## ITT Estimands for $W$

- ▶ The average causal effect of assignment on  $W_i$

$$\widehat{\text{ITT}}_W = \bar{W}_1^{\text{obs}} - \bar{W}_0^{\text{obs}}$$

where  $z = 0, 1$ ,  $N_z = \sum_{i=1}^N 1_{Z_i=z}$ ,  $\bar{W}_z^{\text{obs}} = \sum_{i:Z_i=z} W_i^{\text{obs}} / N_z$

- ▶ with (Neyman) sampling variance estimated as

$$\widehat{\text{V}}(\widehat{\text{ITT}}_W) = \frac{s_{Y,1}^2}{N_1} + \frac{s_{Y,0}^2}{N_0}$$

where

$$s_{W,z}^2 = \sum_{i:Z_i=z} (W_i^{\text{obs}} - \bar{W}_z^{\text{obs}})^2 / (N_z - 1) = \bar{W}_z (1 - \bar{W}_z) / (N_z - 1).$$

## ITT Estimands for $Y$

- ▶ The difference in average outcomes by assignment status,

$$\widehat{\text{ITT}}_Y = \bar{Y}_1^{\text{obs}} - \bar{Y}_0^{\text{obs}}$$

where  $z = 0, 1$ ,  $N_z = \sum_{i=1}^N \mathbf{1}_{Z_i=z}$ ,  $\bar{Y}_z^{\text{obs}} = \sum_{i:Z_i=z} Y_i^{\text{obs}} / N_z$

- ▶ with (Neyman) sampling variance estimated as

$$\widehat{\text{V}}(\widehat{\text{ITT}}) = \frac{s_{W,0}^2}{N_0} + \frac{s_{W,1}^2}{N_1}$$

where  $s_{Y,z}^2 = \sum_{i:Z_i=z} (Y_i^{\text{obs}} - \bar{Y}_z^{\text{obs}})^2 / (N_z - 1)$

## 24.5 Instrumental Variables

- ▶ Main results of this chapter
- ▶ Consider assumptions underlying instrument variables to draw inferences about the relation  $W_i$  and  $Y_i$ 
  - Exclusion Restrictions
  - Monotonicity Assumption

## Exclusion Restrictions

- ▶ **Assumption 24.2 (Exclusion Restriction for Nevertakers)** For all units  $i$  with  $G_i = nt$ ,

$$Y_i(0, 0) = Y_i(1, 0)$$

- ▶ **Assumption 24.3 (Exclusion Restriction for Alwaysstakers)** For all units  $i$  with  $G_i = at$ ,

$$Y_i(0, 1) = Y_i(1, 1)$$

- ▶ **Assumption 24.4 (Exclusion Restriction for Compliers)** For all units  $i$  with  $G_i = co$ ,

$$Y_i(0, w) = Y_i(1, w)$$

for both levels of the treatment  $w$

- ▶ **Assumption 24.5 (Exclusion Restriction for Defiers)** For all units  $i$  with  $G_i = df$ ,

$$Y_i(0, w) = Y_i(1, w)$$

for both levels of the treatment  $w$

## ITT Estimands for $Y$

$$\begin{aligned}\text{ITT}_Y &= \mathbb{E}_{\text{sp}} [Y(1, W(1)) - Y(0, W(0))] \\ &= \sum_{g \in \{\text{co}, \text{nt}, \text{at}, \text{df}\}} \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0)) \mid G_i = g] \cdot \Pr_{\text{sp}} (G_i = g) \\ &= \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0)) \mid G_i = \text{co}] \cdot \Pr_{\text{sp}} (G_i = \text{co}) \\ &\quad + \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0)) \mid G_i = \text{nt}] \cdot \Pr_{\text{sp}} (G_i = \text{nt}) \\ &\quad + \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0)) \mid G_i = \text{at}] \cdot \Pr_{\text{sp}} (G_i = \text{at}) \\ &\quad + \mathbb{E}_{\text{sp}} [Y_i(1, W_i(1)) - Y_i(0, W_i(0)) \mid G_i = \text{df}] \cdot \Pr_{\text{sp}} (G_i = \text{df}) \\ &= \mathbb{E}_{\text{sp}} [Y_i(1, 1) - Y_i(0, 0) \mid G_i = \text{co}] \cdot \pi_{\text{co}} \\ &\quad - \mathbb{E}_{\text{sp}} [Y_i(0, 1) - Y_i(1, 0) \mid G_i = \text{df}] \cdot \pi_{\text{df}}\end{aligned}$$



► **Assumption 24.8 (Monotonicity/No Defiers)**

$$W_i(1) \geq W_i(0)$$

► With assumptions 24.4 and 24.8

$$\text{ITT}_Y = \mathbb{E}_{\text{SP}} [Y_i(1) - Y_i(0) \mid G_i = \text{CO}] \cdot \pi_{\text{CO}}$$

► **Theorem 24.1 (Local Average Treatment Effect)**

with Assumptions 24.1-24.4 and 24.8 hold.

$$\tau_{\text{late}} = \frac{\text{ITT}_Y}{\text{ITT}_W} = \mathbb{E}_{\text{SP}} [Y_i(1) - Y_i(0) \mid G_i = \text{CO}]$$

## Conclusion

- ▶ Introduce types of noncompliance
- ▶ Extend to two-sided noncompliance cases
  - Completely randomized experiments
  - Exclusion restrictions and monotonicity assumption

The End