

# Lecture Notes: Econometrics II

Based on lectures by [Marko Mlikota](#) in Spring semester, 2025

Draft updated on February 25, 2025

These lecture notes were taken in the course *Econometrics II* taught by [Marko Mlikota](#) at Graduate of International and Development Studies, Geneva as part of the International Economics program (Semester II, 2024).

Currently, these are just drafts of the lecture notes. There can be typos and mistakes anywhere. So, if you find anything that needs to be corrected or improved, please inform at [jingle.fu@graduateinstitute.ch](mailto:jingle.fu@graduateinstitute.ch).

<h2>Contents</h2>
-------------------

1.	Review of Econometrics I	1
1.1.	Basic assumptions . . . . .	1
1.2.	Endogeneity . . . . .	1
2.	Causal Inference	4
2.1.	Potential Outcomes Framework . . . . .	4
	Recommended Resources	7

Lecture 1.

## Review of Econometrics I

### 1.1 Basic assumptions

As we know,

$$\hat{\beta} = (X'X)^{-1}X'y \xrightarrow{P} \beta$$

if

1. Model is correctly specified:  $y_i = x_i'\beta + u_i$
2.  $X$  is full rank
3.  $\mathbb{E}[x_i u_i] = 0$ :  $x_i$  is exogenous.
4. Unbiased CIA:  $\mathbb{E}[u_i | x_i] = 0$

**Theorem 1.1.1** (Frisch-Waugh-Lovell (FWL) theorem).

Recall:  $\hat{Y} = X\hat{\beta} = X(X'X)^{-1}X'Y = P_X Y$ ,  $Y = \hat{Y} + \hat{U} \rightarrow \hat{U} = (I - P_X)Y = M_X Y$ .

Take  $Y = X_1\beta_1 + X_2\beta_2 + U = X\beta' + U$ , let  $P_1 = X_1(X_1'X_1)^{-1}X_1'$ ,  $M_1 = I - P_1$ .

And write  $M_1 Y = M_1 X_2 \beta_2 + M_1 U$ , then

$$\hat{\beta}_{2,OLS} = \hat{b}.$$

### 1.2 Endogeneity

Three reasons for endogeneity:

1. Measurement error:  $x_i$  is measured with error.

Assume the true Regression is:  $y_i = x_i^{*'}\beta + \varepsilon_i$ ,  $\mathbb{E}[x_i^* \varepsilon_i] = 0$ , we run:  $y_i = x_i'\beta + u_i$ ,  $x_i = x_i^* + v_i$ ,  $u_i = \varepsilon_i - v_i'\beta$ .

$$\begin{aligned} \mathbb{E}[x_i u_i] &= \underbrace{\mathbb{E}[x_i \varepsilon_i]}_0 - \mathbb{E}[x_i v_i']\beta \\ &= -\mathbb{E}[(x_i^* + v_i)v_i']\beta \\ &= \underbrace{-\mathbb{E}[x_i^* v_i']}_0 \beta - \mathbb{E}[v_i v_i']\beta \\ &= -\mathbb{E}[v_i v_i']\beta \end{aligned}$$

2. Simultaneity(Reverse causality):  $x_i$  is endogenous.

$$y_i = x_i'\beta + u_i = x_{i1}^*\beta_1 + x_{i2}\beta_2 + u_i, \quad x_i = z_i'\gamma + y_i\delta + v_i.$$

3. Omitted variables:  $x_i$  is correlated with  $u_i$ .

The true regression is:  $y_i = x_i'\beta + w_i'\delta + \varepsilon_i$ ,  $\mathbb{E}[x_i \varepsilon_i] \neq 0$ ,  $\mathbb{E}[w_i \varepsilon_i] = 0$ .

We run:  $y_i = x_i' \beta + u_i$ , then

$$\begin{aligned}\mathbb{E}[x_i u_i] &= \mathbb{E}[x_i (w_i' \delta + \varepsilon_i)] \\ &= \mathbb{E}[x_i w_i'] \delta + \underbrace{\mathbb{E}[x_i \varepsilon_i]}_0\end{aligned}$$

For our general regression model  $y_i = x_i' \beta + u_i$ , we have  $\mathbb{E}[x_i u_i] \neq 0$ , thus  $\hat{\beta}_{OLS} \xrightarrow{P} \beta$  doesn't hold.

We take  $z_i \in \mathbb{R}^r$ , which is a good IV if:

1. Relevance:  $\mathbb{E}[z_i x_i] \neq 0$ ;
2. Exogeneity:  $\mathbb{E}[z_i u_i] = 0$ .

Then, we have the 2SLS method:

**Definition 1.2.1** (2SLS Method).

1. Estimate:  $x_i = z_i' \gamma + e_i \Rightarrow \hat{\gamma} = (Z'Z)^{-1} Z'X \Rightarrow \hat{X} = Z' \hat{\gamma} = P_Z X$ ;
2. Estimate:  $y_i = \hat{x}_i' \beta + u_i^*$ .

$$\begin{aligned}\hat{\beta}_{2SLS} &= (\hat{X}' \hat{X})^{-1} \hat{X}' Y \\ &= ((P_Z X)' P_Z X)^{-1} (P_Z X)' Y \\ &= (X' P_Z X)^{-1} X' P_Z Y \\ &= (X' Z (Z' Z)^{-1} Z' X)^{-1} X' Z (Z' Z)^{-1} Z' Y \\ &= \beta + (X' Z (Z' Z)^{-1} Z' X)^{-1} X' Z (Z' Z)^{-1} Z' u \\ &\xrightarrow{P} \beta + Q_{xz}^{-1} \mathbb{E}[x_i z_i'] \mathbb{E}[z_i z_i'] \mathbb{E}[z_i u_i] \\ &= \beta.\end{aligned}$$

$$\begin{aligned}\mathbb{V}[\hat{\beta}_{2SLS} | X, Z] &= \mathbb{V}[(X' P_Z X)^{-1} X' P_Z U | X, Z] \\ &= (X' P_Z X)^{-1} \mathbb{V}[X' P_Z U | X, Z] (X' P_Z X)^{-1} \\ &= (X' P_Z X)^{-1} X' P_Z \mathbb{V}[U] P_Z X (X' P_Z X)^{-1} \\ &= (X' P_Z X)^{-1} \sigma^2\end{aligned}$$

As we know  $\mathbb{V}[\hat{\beta}_{OLS}] = (X' X)^{-1} \sigma^2$ ,

$$\begin{aligned}\mathbb{V}[\hat{\beta}_{OLS}]^{-1} - \mathbb{V}[\hat{\beta}_{2SLS}]^{-1} &= (\sigma^2)^{-1} X' X - (\sigma^2)^{-1} X' P_Z X \\ &= (\sigma^2)^{-1} X' (I - P_Z) X \\ &= (\sigma^2)^{-1} X' M_Z X \\ &= \sigma^{-2} \underbrace{(M_Z X)'}_{\hat{E}} M_Z X \\ &= \sigma^{-2} SSR_{1SLS}.\end{aligned}$$

**Theorem 1.2.1** (Anderson-Rubin Method).

$$y_i = x_i' \beta_0 + u_i, \mathbb{E}[z_i u_i] = 0, y_i - x_i' \beta = \delta z_i + v_i. \Rightarrow \hat{\delta}(\beta) = (Z' Z)^{-1} Z' (Y - X \beta) \rightarrow \hat{\delta}(\beta_0) =$$

$(Z'Z)^{-1}Z'U$ . For many  $\beta$ s, test:  $H_0 : \delta(\beta) = 0$ , e.g. using t-test.

$$T_t = \frac{\hat{\delta}(\beta)}{se(\hat{\delta}(\beta))} \sim \mathbf{N}(0, 1)$$

The 90% CI for  $\beta$  is the set of  $\beta$ s at which  $\delta(\beta) = 0$  cannot be rejected at 90% confidence level.

## Causal Inference

### 2.1 Potential Outcomes Framework

**Definition 2.1.1** (Stable Unit Treatment Value Assumption (SUTVA)).

$$y_i = \begin{cases} y_{0i} & d_i = 0 \\ y_{1i} & d_i = 1 \end{cases}$$

Causal effect of  $d_i$  on  $y_i$  for individual  $i$ :  $y_{1i} - y_{0i}$ .

$$y_i = d_i y_{1i} + (1 - d_i) y_{0i}$$

SUTVA(2.1.1) ensures that the individual treatment effect is well defined.

For a population, we know that  $\mathbb{E}[d_i], \mathbb{E}[y_i], \mathbb{E}[y_{0i}], \mathbb{E}[y_{1i}]$  exist, we can define the treatment conditional expectations:

$$\mathbb{E}[y_i | d_i = 1], \mathbb{E}[y_{0i} | d_i = 1], \mathbb{E}[y_{1i} | d_i = 1] = \mathbb{E}[y_i | d_i = 1]$$

that denote the averages of the outcome  $y_i$ .

Analogously, we can define the control conditional expectations:

$$\mathbb{E}[y_i | d_i = 0], \mathbb{E}[y_{0i} | d_i = 0] = \mathbb{E}[y_i | d_i = 0], \mathbb{E}[y_{1i} | d_i = 0]$$

for the non-treated subpopulation.

Then, we can define the Average Treatment Effect (ATE), the Average Treatment Effect for the Treatment-Group (ATT) and the Average Treatment Effect for the Control-Group (ATC) as distinct objects:

$$\text{ATE} = \mathbb{E}[y_{1i} - y_{0i}]$$

$$\text{ATT} = \mathbb{E}[y_{1i} - y_{0i} | d_i = 1]$$

$$\text{ATC} = \mathbb{E}[y_{1i} - y_{0i} | d_i = 0]$$

$$\mathbb{E}[z] = \mathbb{E}[z | d = 1] \mathbb{P}[d = 1] + \mathbb{E}[z | d = 0] \mathbb{P}[d = 0] = \mathbb{E}[\mathbb{E}[z | d]].$$

For sample,  $\{d_i, y_i\}_{i=1}^n = \{d_i, y_{d_i, i}\}_{i=1}^n$ , because  $y_i = y_{1i} d_i + y_{0i} (1 - d_i)$ .

$N = \{i = 1, 2, \dots, n\}$ ,  $N_1 = \{i \in N : d_i = 1\} \leftarrow n_1 = |N_1|$ ,  $N_0 = \{i : d_i = 0\} \leftarrow n_0 = |N_0|$ .

$$\frac{1}{n_1} \sum_{i \in N_1} y_i = \frac{1}{n_1} \sum_{i \in N_1} y_{1i} \xrightarrow{p} \mathbb{E}[y_{1i} | d_i = 1] = \mathbb{E}[y_i | d_i = 1]$$

$$\frac{1}{n_0} \sum_{i \in N_0} y_i = \frac{1}{n_0} \sum_{i \in N_0} y_{0i} \xrightarrow{p} \mathbb{E}[y_{0i} | d_i = 0] = \mathbb{E}[y_i | d_i = 0]$$

$$\frac{1}{n_1} \sum_{i \in N_1} y_i - \frac{1}{n_0} \sum_{i \in N_0} y_i \xrightarrow{p} \mathbb{E}[y_{1i} | d_i = 1] - \mathbb{E}[y_{0i} | d_i = 0] = \text{ATE} = \text{ATT} = \text{ATC}.$$

We define the difference of treated and non-treated as: *Naive Difference*.

$$\begin{aligned} \text{ND} &= \mathbb{E}[y_{1i}|d_i = 1] - \mathbb{E}[y_{0i}|d_i = 0] \\ &= \mathbb{E}[y_{1i}|d_i = 1] - \mathbb{E}[y_{0i}|d_i = 1] + \mathbb{E}[y_{0i}|d_i = 1] - \mathbb{E}[y_{0i}|d_i = 0] \\ &= \text{ATT} + \mathbb{E}[y_{0i}|d_i = 1] - \mathbb{E}[y_{0i}|d_i = 0] \end{aligned}$$

For LRM,  $y_i = \beta_0 + \beta_1 d_i + u_i$ ,

$$\begin{aligned} \text{ND} &= \mathbb{E}[y_i|d_i = 1] - \mathbb{E}[y_i|d_i = 0] \\ &= \mathbb{E}[\beta_0 + \beta_1 + u_i|d_i = 1] - \mathbb{E}[\beta_0 + u_i|d_i = 0] \\ &= \beta_1 + \mathbb{E}[u_i|d_i = 1] - \mathbb{E}[u_i|d_i = 0] \end{aligned}$$

$$\{Y_d\} \perp\!\!\!\perp D \mid X \Rightarrow \{Y_d\} \perp\!\!\!\perp D \mid \pi(X), \quad D \perp\!\!\!\perp X \mid \pi(X)$$



## Appendix

## Recommended Resources

### Books

- [1] James H. Stock and Mark W. Watson. *Introduction to Econometrics*. 4th ed. New York: Pearson, 2003
- [2] Jeffrey M. Wooldridge. *Introductory Econometrics: A Modern Approach*. 7th ed. Cengage Learning, 2020
- [3] Bruce E. Hansen. *Econometrics*. Princeton, New Jersey: Princeton University Press, 2022
- [4] Fumio Hayashi. *Econometrics*. Princeton, New Jersey: Princeton University Press, 2000
- [5] Jeffrey M. Wooldridge. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, Massachusetts: The MIT Press, 2010
- [6] Joshua Chan et al. *Bayesian Econometric Methods*. 2nd ed. Cambridge, United Kingdom: Cambridge University Press, 2019
- [7] Badi H. Baltagi. *Econometric Analysis of Panel Data*. 6th ed. Cham, Switzerland: Springer, 2021
- [8] James D. Hamilton. *Time Series Analysis*. Princeton, New Jersey: Princeton University Press, 1994. ISBN: 9780691042893
- [9] Takeshi Amemiya. *Advanced Econometrics*. Cambridge, MA: Harvard University Press, 1985

### Others

- [10] Roger Bowden. “The Theory of Parametric Identification”. In: *Econometrica* 41.6 (1973), pp. 1069–1074. DOI: [10.2307/1914036](https://doi.org/10.2307/1914036)
- [11] Robert I. Jennrich. “Asymptotic Properties of Non-linear Least Squares Estimators”. In: *The Annals of Mathematical Statistics* 40.2 (1969), pp. 633–643. DOI: [10.1214/aoms/1177697731](https://doi.org/10.1214/aoms/1177697731)
- [12] Michael P. Keane. “A Note on Identification in the Multinomial Probit Model”. In: *Journal of Business & Economic Statistics* 10.2 (1992), pp. 193–200. DOI: [10.1080/07350015.1992.10509906](https://doi.org/10.1080/07350015.1992.10509906)
- [13] Thomas J. Rothenberg. “Identification in Parametric Models”. In: *Econometrica* 39.3 (1971), pp. 577–591. DOI: [10.2307/1913267](https://doi.org/10.2307/1913267)
- [14] George Tauchen. “Diagnostic Testing and Evaluation of Maximum Likelihood Models”. In: *Journal of Econometrics* 30 (1985), pp. 415–443. DOI: [10.1016/0304-4076\(85\)90149-6](https://doi.org/10.1016/0304-4076(85)90149-6)
- [15] Abraham Wald. “Note on the Consistency of the Maximum Likelihood Estimate”. In: *The Annals of Mathematical Statistics* 20.4 (1949), pp. 595–601. DOI: [10.1214/aoms/1177729952](https://doi.org/10.1214/aoms/1177729952)
- [16] Halbert White. “Maximum Likelihood Estimation of Misspecified Models”. In: *Econometrica* 50.1 (1982), pp. 1–25. DOI: [10.2307/1912526](https://doi.org/10.2307/1912526)