

# Lecture Notes: Econometrics II

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These lecture notes were taken in the course *Econometrics II* taught by [Marko Mlikota](#) at Graduate Institute 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).

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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

We say that there's endogeneity in the linear model

$$y_i = x_i'\beta + u_i$$

if  $\beta$  is the parameter of interest and

$$\mathbb{E}[x_i u_i] \neq 0.$$

This is a core problem in econometrics and largely differentiates the field from statistics.

Endogeneity implies that the least squares estimator is inconsistent for the structural parameter. Indeed, under i.i.d. sampling, least squares is consistent for the projection coefficient.

$$\hat{\beta} \xrightarrow{P} \beta + \left(\mathbb{E}[XX']\right)^{-1} \mathbb{E}[XU] \neq \beta$$

The inconsistency of least squares is typically referred to as **endogeneity bias** or **estimation bias** due to endogeneity.

Commonly, there are three reasons for endogeneity:

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

Suppose our true Regression is:  $y_i = x_i^{*\prime} \beta + \varepsilon_i$ ,  $\mathbb{E}[x_i^* \varepsilon_i] = 0$ ,  $\beta$  is the structural parameter. But,  $x_i^{*}$  is not observed. Instead, we observe:  $x_i = x_i^* + v_i$ , where  $v_i$  is the measurement error, independent of  $x_i^*$  and  $\varepsilon_i$ :  $\mathbb{E}[x_i^* v_i'] = 0$ ,  $\mathbb{E}[v_i \varepsilon_i] = 0$ <sup>1</sup>.

The model  $x_i = x_i^* + v_i$  with  $x_i^*$  and  $v_i$  uncorrelated, and  $\mathbb{E}[v_i] = 0$  is known as the **classical measurement error model**. This means that  $x_i$  is a noisy but unbiased estimate of  $x_i^*$ . By substitution we can express  $y_i$  as a function of the observed variable  $x_i$ .

$$y_i = x_i^{*\prime} \beta + \varepsilon_i = (x_i - v_i)' \beta + \varepsilon_i = x_i' \beta + u_i$$

where  $u_i = \varepsilon_i - v_i' \beta$ .

This means that  $(y_i, x_i)$  satisfy the linear equation  $y_i = x_i' \beta + u_i$  with an error  $u_i$ . But this error is not a projection error.

$$\begin{aligned} \mathbb{E}[x_i u_i] &= \underbrace{\mathbb{E}[x_i \varepsilon_i]}_0 - \mathbb{E}[x_i v_i'] \beta \\ &= -\mathbb{E}[(x_i^* + v_i) v_i'] \beta \\ &= -\underbrace{\mathbb{E}[x_i^* v_i']}_0 \beta - \mathbb{E}[v_i v_i'] \beta \\ &= -\mathbb{E}[v_i v_i'] \beta \neq 0 \end{aligned}$$

if  $\mathbb{E}[v_i v_i'] \neq 0$  and  $\beta \neq 0$ .

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: The most prominent cause of endogeneity are omitted variables (OVs).

Suppose the true regression is:  $y_i = x_i' \beta + w_i' \delta + \varepsilon_i$ , where exogeneity holds:  $\mathbb{E}[x_i \varepsilon_i] = 0$ ,  $\mathbb{E}[w_i \varepsilon_i] = 0$ .

If we omit  $w_i$  and instead estimates:

$$y_i = x_i' \beta + u_i$$

where  $u_i = w_i' \delta + \varepsilon_i$ , then in this misspecified model, exogeneity is only given if  $x_i$  and  $w_i$  are uncorrelated, since:

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

Since  $\hat{\beta} - \beta \xrightarrow{p} \mathbb{E}[x_i x_i']^{-1} \mathbb{E}[x_i u_i]$ , we can assess the sign and size of the asymptotic bias based on the signs of correlation between  $x_i$  and  $w_i$ .

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.

To consistently estimate  $\beta$ , we require additional assumptions. One type of information which is commonly used in economics is the **instruments**.

#### Definition 1.2.1 (Instrumental Variable).

We take  $z_i \in \mathbb{R}^r$  as an instrumental variable if:

$$\begin{aligned} \mathbb{E}[z_i u_i] &= 0 \\ \mathbb{E}[z_i x_i] &\neq 0 \end{aligned}$$

<sup>1</sup>This is an example of a latent variable model, where “latent” refers to an unobserved structural variable.

$$\mathbb{E}[z_i z_i'] > 0$$

$$\text{rank}\left(\mathbb{E}[z_i z_i']\right) = k \leq r \quad 2$$

We say that the model is just-identified if  $k = r$  and over-identified if  $k < r$ .

### 1.2.1 Instrumental Variables and 2SLS

Then, we have the 2SLS method:

**Definition 1.2.2 (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:  $y_i = \hat{x}_i' \beta + u_i^*$ .

$$\begin{aligned} \hat{\beta}_{2SLS} &= (\hat{X}' \hat{X})^{-1} \hat{X}' Y \\ &= ((P_Z X)' P_Z X)^{-1} (P_Z X)' Y \\ &= (X' P_Z X)^{-1} X' P_Z Y \\ &= (X' Z (Z' Z)^{-1} Z' X)^{-1} X' Z (Z' Z)^{-1} Z' Y \\ &= \beta + (X' Z (Z' Z)^{-1} Z' X)^{-1} X' Z (Z' Z)^{-1} Z' u \\ &= \beta + (Z' X)^{-1} (Z' Z) (X' Z)^{-1} X' Z (Z' Z)^{-1} Z' u \quad 3 \\ &= \beta + (Z' X)^{-1} Z' u \\ &\xrightarrow{p} \beta. \end{aligned}$$

To compute  $\hat{\beta}_{2SLS}$ , we need  $Z'Z$  to be full rank, which requires us to have more observations than IVs.

Ideally,  $z_i$  should be as highly correlated with  $x_i$  as possible, but uncorrelated with  $u_i$ . To see this, we find the variance of  $\hat{\beta}_{2SLS}$

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

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

$$\begin{aligned} \mathbb{V}[\hat{\beta}_{OLS}]^{-1} - \mathbb{V}[\hat{\beta}_{2SLS}]^{-1} &= (\sigma^2)^{-1} X' X - (\sigma^2)^{-1} X' P_Z X \\ &= (\sigma^2)^{-1} X' (I - P_Z) X \\ &= (\sigma^2)^{-1} X' M_Z X \\ &= \sigma^{-2} \underbrace{(M_Z X)'}_{\hat{E}} M_Z X \\ &= \sigma^{-2} SSR_{1SLS} > 0. \end{aligned}$$

This means that the variance of 2SLS estimator is larger than that of the OLS.

By the usual arguments, the asymptotic analysis reveals that:

$$\sqrt{n}(\hat{\beta}_{2SLS} - \beta) \xrightarrow{p} \mathcal{N}(0, V_{2SLS})$$

where

$$V_{2SLS} = Q_{XZ}^{-1} X'Z (Z'Z)^{-1} Z'UU'Z (Z'Z)^{-1} (X'Z)' Q_{XZ}^{-1}$$

where  $Q_{XZ} = (Z'X)(Z'Z)^{-1}(X'Z)$

As usual, we can estimate it by replacing  $u_i$  with  $\hat{u}_i$  and expectation operators with population means. Thereby, it's important to note that  $u_i \neq u_i^*$ , and to obtain  $\hat{u}_i$ , we don't use  $\hat{x}_i$ , but  $x_i$ :

$$\hat{u}_i = y_i - x_i' \hat{\beta}_{2SLS}$$

Under homoskedasticity,  $V_{2SLS} = \sigma^2 Q_{XZ}^{-1}$ , which we estimate using  $\hat{\sigma}^2 = \frac{1}{n} \sum_i u_i^2$ .

## 1.2.2 Weak Identification in IV Models

If the correlation between  $x_i$  and  $z_i$  is weak, then we say it's a **weak instrument**. Under weak IVs, the finite sample distribution of  $\hat{\beta}_{2SLS}$  may not assemble the asymptotic property.

In absence of an asymptotic distribution, we can conduct inference using its numerical approximation via bootstrapping. Or alternatively, we can construct a confidence set for  $\beta$  using the following procedure of Anderson and Rubin (1949).

The method is based on the idea that, for  $\beta = \beta_0$ , the auxiliary regression  $y_i - x_i'\beta = \delta z_i + v_i$  should yield  $\delta = 0$ , because  $y_i - x_i'\beta_0 = u_i$  and  $u_i$  is uncorrelated with  $z_i$ .

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

For a given  $\beta_0$ , we get:

$$\sqrt{n}\hat{\delta}(\beta_0) = \sqrt{n}(Z'Z)^{-1}Z'(Y - X\beta_0) = (Z'Z)^{-1}\sqrt{n}Z'U \xrightarrow{d} \mathcal{N}\left(0, \frac{\sigma_u^2}{\mathbb{E}(z_i^2)}\right)$$

which allows us to test  $\mathcal{H}_0 : \delta = 0$ . For many  $\beta$ s, test:  $\mathcal{H}_0 : \delta(\beta) = 0$ , e.g. using t-test.

$$T_t = \frac{\hat{\delta}(\beta_0)}{se(\hat{\delta}(\beta_0))} = \frac{\hat{\delta}_0}{\sqrt{\hat{\sigma}_u^2/Z'Z}} \xrightarrow{d} \mathcal{N}(0, 1)$$

The 90% CI for  $\beta$  is the set of  $\beta$ s at which  $\delta(\beta) = 0$  cannot be rejected at 90% confidence level. A confidence set for  $\beta$  is given by taking all  $\beta_0$  such that  $\mathcal{H}_0 : \delta = 0$  cannot be rejected.

### Remark (About Anderson-Rubin (AR) Test).<sup>a</sup>

Consider our model

$$\begin{aligned} y &= X\beta + u, \\ X &= Z\Pi + v, \end{aligned}$$

where  $X$  is one-dimensional and test for hypothesis  $H_0 : \beta = \beta_0$ . Under the null, vector  $y - X\beta$  is equal to the error  $u_t$  and is uncorrelated with  $Z$  (due to exogeneity of instruments). The suggested statistics is:

$$AR(\beta_0) = \frac{(y - X\beta)'P_Z(y - X\beta)}{(y - X\beta)'M_Z(y - X\beta)/(T - k)}.$$

here  $P_Z = Z(Z'Z)^{-1}Z'$ ,  $M_Z = I - P_Z$ .

The distribution of AR does not depend on  $\mu$  asymptotically  $AR \rightarrow \chi_k^2/k$ . The formula may remind

you of the J-test for over-identifying restrictions. It would be a J-test if one were to plug in  $\hat{\beta}_{TSLS}$ . In a more general situation of more than one endogenous variable and/or included exogenous regressors AR statistic is F-statistic testing that all coefficients on  $Z$  are zero in the regression of  $y - \beta_0 X$  on  $Z$  and  $W$ .

Note, that one tests all coefficients  $\beta$  simultaneously (as a set) in a case of more than one endogenous regressor. AR confidence set One can construct a confidence set robust towards weak instruments based on the AR test by inverting it. That is, by finding all  $\beta$  which are not rejected by the data. In this case, it is the set :

$$CI = \{\beta_0 : AR(\beta_0) < \chi_{k,1-\alpha}^2\}.$$

The nice thing about this procedure is that solving for the confidence set is equivalent to solving a quadratic inequality. This confidence set can be empty with positive probability (caution!).

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<sup>a</sup>Retrieved from MIT14.384 Time Series Analysis, Fall 2007 Professor Anna Mikusheva, Lecture 7-8, [https://ocw.mit.edu/courses/14-384-time-series-analysis-fall-2013/365cba34145fa204731e9df202d4771e\\_MIT14\\_384F13\\_lec7and8.pdf](https://ocw.mit.edu/courses/14-384-time-series-analysis-fall-2013/365cba34145fa204731e9df202d4771e_MIT14_384F13_lec7and8.pdf)



Lecture 2.

## Causal Inference

Rubin (1975[11]) and Holland (1986[12]) made up the aphorism[1]:

*“No causation without manipulation”*

Not everybody agrees with this point of view. In our lecture, we’ll define causal effects using the potential outcomes framework (Neyman, 1923[13]; Rubin, 1974[14]).

### 2.1 Potential Outcomes Framework

In this framework, an experiment, or at least a thought experiment, has a treatment, and we are interested in its effect on an outcome or multiple outcomes. Sometimes, the treatment is also called an intervention or a manipulation.

Firstly, we consider an experiment with  $n$  units indexed by  $i = 1, 2, \dots, n$ . We focus on a treatment with two levels:

$$d_i = \begin{cases} 0 & \text{control} \\ 1 & \text{treatment} \end{cases}$$

We seek to identify the causal effect of treatment  $d_i$  on some outcome  $y_i$ . For each  $i$ , the outcome of interest  $y_i$  has two versions:

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

This notation emphasizes that  $y_{di}$  is the realization of the outcome  $y_i$  that would materialize if unit  $i$  received treatment  $d_i = d$ .

Neyman (1923[13]) first used this notation. It seems intuitive but has some hidden assumptions. Rubin (1980[15]) made the following clarifications on the hidden assumptions.

**Assumption 2.1.1 (No interference).**

Unit  $i$ ’s potential outcomes do not depend on other units’ treatments. This is sometimes called the no-interference assumption.

**Assumption 2.1.2 (Consistency).**

There are no other versions of the treatment. Equivalently, we require that the treatment levels be well-defined, or have no ambiguity at least for the outcome of interest. This is sometimes called the consistency assumption.

The causal effect of the treatment on the  $i$ -th unit is then defined as:

$$\Delta_i = y_{1i} - y_{0i}$$

These potential outcomes are constants at the level of unit  $i$ .

**Remark** (Problem of causal inference).

The fundamental problem in causal inference is that only one treatment can be assigned to a given individual, and so only one of  $y_{0i}$  and  $y_{1i}$  can be observed. Thus  $\Delta_i$  can never be observed.

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

Rubin (1980[15]) called the Assumptions 2.1.1 and 2.1.2 above together the *Stable Unit Treatment Value Assumption (SUTVA)*.

The observed outcome of unit  $i$  is a function of the potential outcomes and the treatment indicator, we can write:

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

In principle, by virtue of being (discrete) RVs, both  $d_i$  and  $y_i$  each have a distribution function, which, together with their possible realizations, defines various moments. However, their unconditional probabilities and moments at the level of unit  $i$  is not of interest. Only the conditional probabilities of  $y_i$  given  $d_i$  is of interest.

**Remark** (Rubin (2005[16])).

Under SUTVA, Rubin (2005) called the  $n \times 2$  matrix of potential outcomes the Science Table:

$i$	$y_{1i}$	$y_{0i}$
1	$y_{11}$	$y_{01}$
2	$y_{12}$	$y_{02}$
$\vdots$	$\vdots$	$\vdots$
$n$	$y_{1n}$	$y_{0n}$

Due to the fundamental contributions of Neyman and Rubin to statistical causal inference, the potential outcomes framework is sometimes referred to as the Neyman Model, the Neyman-Rubin Model, or the Rubin Causal Model. Causal effects are functions of the Science Table. Inferring individual causal effects

$$\tau_i = y_{1i} - y_{0i}, \quad (i = 1, \dots, n)$$

is fundamentally challenging because we can only observe either  $y_{1i}$  or  $y_{0i}$ , for each unit  $i$ , that is, we can observe only half of the Science Table.

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

Now, although  $\Delta_i$  itself is unobservable, we can (perhaps remarkably) use randomized experiments to learn certain properties of it. The expectations  $\mathbb{E}[y_{0i}]$  and  $\mathbb{E}[y_{1i}]$  denote the average potential outcomes across unit  $i$  in population.

In particular, large randomized experiments let us recover the **Average Treatment Effect (ATE)**:

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

For a population, 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.

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

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

### 2.1.1 Identification of Causal Effects

Now, suppose we observe treatments and outcomes over a random sample  $n$  from the overall population,  $\{d_i, y_i\}_{i=1}^n = \{d_i, y_{d_i}\}_{i=1}^n$ , as either  $y_I = y_{0i}$ , or  $y_i = y_{1i}$ .

Let  $n_w = |\{i : d_i = w\}|$  be the size of sets of units in our sample who received and did not receive treatment, respectively. This means that: while we observe a sample of size  $n$  of  $d_i$  and  $y_i$  from the overall population, we are observing a sample of size  $n_0$  of realizations of  $y_{0i}$  from the non-treated subpopulation and a sample of size  $n_1$  of realizations of  $y_{1i}$  from the treated subpopulation.

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

Based on this data, we can use the analogy principle to consistently estimate the first term in the ATT formula and the second term in the ATC formula:

$$\begin{aligned} \frac{1}{n_1} \sum_{i \in N_1} y_i &= \frac{1}{n_1} \sum_{i \in N_1} y_{1i} \xrightarrow{p} \mathbb{E}[y_{1i}|d_i = 1] = \mathbb{E}[y_i|d_i = 1] \\ \frac{1}{n_0} \sum_{i \in N_0} y_i &= \frac{1}{n_0} \sum_{i \in N_0} y_{0i} \xrightarrow{p} \mathbb{E}[y_{0i}|d_i = 0] = \mathbb{E}[y_i|d_i = 0] \end{aligned}$$

Without further assumptions, we cannot identify the remaining terms. Firstly, we cannot observe  $\mathbb{E}[y_{0i}|d_i = 1]$  and  $\mathbb{E}[y_{1i}|d_i = 0]$  because we do not observe  $y_{0i}$  for treated units, and we do not observe  $y_{1i}$  for non-treated units. Secondly, we can not observe  $\mathbb{E}[y_{1i}]$  and  $\mathbb{E}[y_{0i}]$  because both  $N_1$  and  $N_0$  are random samples from the overall population. As a result, the ATE is in general not identified from our data!

We can define the the difference-in-means estimator as:

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

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

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

## Panel Data Analysis

Economists traditionally use the term **panel data** to refer to data structures consisting of observations on individuals for multiple time periods. There are several distinct advantages of panel data relative to cross-section data:

1. Possibility of controlling for unobserved time-invariant endogeneity without the use of instrumental variables
2. Possibility of allowing for broader forms of heterogeneity
3. Modeling dynamic relationships and effects

It's typical to index observations by both the individual  $i$  and the time period,  $t$ , thus  $y_{it}$  denotes a variable for individual  $i$  in time  $t$ , where  $n = 1, \dots, N$ ,  $t = 1, \dots, T$ .

### Definition 3.0.1 (Balanced and Unbalanced Panel Data[2]).

When observations are available on all individuals for the same time periods we say that the panel is **balanced**. In this case there are an equal number  $T$  of observations for each individual and the total number of observations is  $n = NT$ .

When different time periods are available for the individuals in the sample we say that the panel is **unbalanced**. This is the most common type of panel data set. It does not pose a problem for applications but does make the notation cumbersome and also complicates computer programming.

## 3.1 Incidental Parameters Problem

### 3.1.1 Pooled OLS Estimation

Suppose we are estimating the following panel data regression:

$$y_{it} = \alpha + x'_{it}\beta + u_{it}, \quad \mathbb{E}[u_{it}|x_{it}] = 0, \quad \mathbb{V}[u_{it}|x_{it}] = \sigma^2$$

Omitting the distinction between intercept and slope, we can write the model as:

$$y_{it} = \tilde{x}'_{it}\tilde{\beta} + u_{it}$$

$$\tilde{x}_{it} = \begin{bmatrix} 1 \\ x_{it} \end{bmatrix}, \quad \tilde{\beta} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix}$$

where  $i = 1 : n$ ,  $T = 1 : t$ .

Or, we can write the model as:

$$\begin{matrix} y_i & \tilde{X}_i & \tilde{\beta} & u_i \\ T \times 1 & T \times K & K \times 1 & T \times 1 \end{matrix}$$

Using OLS method to estimate  $\tilde{\beta}$ , we have:

$$\min_{\tilde{\beta}} \sum_i \sum_t u_{it}^2 = \min_{\tilde{\beta}} \sum_i u'_i u_i = \min_{\tilde{\beta}} (y_i - \tilde{X}_i \tilde{\beta})' (y_i - \tilde{X}_i \tilde{\beta})$$

The FOC of this equation is:

$$\begin{aligned}
\sum_i -\tilde{X}_i'(y_i - \tilde{X}_i\tilde{\beta}) &= 0 \\
\left(\sum_i \tilde{X}_i'\tilde{X}_i\right)\tilde{\beta} &= \sum_i \tilde{X}_i'y_i \\
\hat{\beta}_{POLLS} &= \left(\sum_i \tilde{X}_i'\tilde{X}_i\right)^{-1} \sum_i \tilde{X}_i'y_i \\
&= \left(\sum_i \sum_t \tilde{x}_{it}\tilde{x}_{it}'\right)^{-1} \left(\sum_i \sum_t \tilde{x}_{it}y_{it}\right) \\
&= \tilde{\beta} + \left(\frac{1}{n} \sum_i \sum_t \tilde{x}_{it}\tilde{x}_{it}'\right)^{-1} \left(\sum_i \sum_t \tilde{x}_{it}u_{it}\right) \\
&\xrightarrow{p} \tilde{\beta} + \mathbb{E}\left[\sum_t \tilde{x}_{it}\tilde{x}_{it}'\right]^{-1} \mathbb{E}\left[\sum_t \tilde{x}_{it}u_{it}\right] \\
&= \tilde{\beta}
\end{aligned}$$

Hence  $\hat{\beta}_{OLS}$  is consistent provided that  $x_{it}$  and  $u_{it}$  are contemporaneously uncorrelated, as  $\mathbb{E}[x_{it}u_{it}] = 0, \forall t$ . The regressors are allowed to be correlated with the past, and future  $u_{it}$ . This occurs when there's feedback loop by which  $y_{i,t-1}$  affects  $x_{it}$ .

In this proof, we show that either  $N \rightarrow \infty$  or  $T \rightarrow \infty$  is sufficient for consistency of  $\hat{\beta}_{POLLS}$ . However, most panel data applications have a large  $n$  and small  $T$  dimension, so standard panel data features  $T$  fixed and  $n \rightarrow \infty$ .

### 3.1.2 Asymptotic Normality

From the analysis of consistency, we know that:

$$\hat{\beta}_{POLLS} = \left(\sum_i \tilde{X}_i'\tilde{X}_i\right)^{-1} \sum_i \tilde{X}_i'y_i$$

Hence:

$$\begin{aligned}
\sqrt{n}(\hat{\beta}_{POLLS} - \tilde{\beta}) &= \left(\frac{1}{n} \sum_i \tilde{X}_i'\tilde{X}_i\right)^{-1} \left(\frac{1}{\sqrt{n}} \sum_i \tilde{X}_i'u_i\right) \\
&\xrightarrow{p} \mathbb{E}[\tilde{X}_i'\tilde{X}_i]^{-1} \xrightarrow{d} \mathcal{N}\left(0, \mathbb{E}\left[\left(\tilde{X}_i'u_i\right)\left(\tilde{X}_i'u_i\right)'\right]\right) \\
&\xrightarrow{d} \mathcal{N}\left(0, \mathbb{E}\left[\tilde{X}_i'\tilde{X}_i\right]^{-1} \mathbb{E}\left[\tilde{X}_i'u_i u_i' \tilde{X}_i\right] \mathbb{E}\left[\tilde{X}_i'\tilde{X}_i\right]\right)
\end{aligned}$$

The above model is homogeneous, which is unattractive, as the data generating process would differ across  $i$ , with some units having a higher level of the outcome variable  $y_{it}$  than others, regardless of covariates  $x_{it}$  (with a higher intercept  $\alpha$ ) or a stronger effect of some covariates  $x_{it,k}$  on  $y_{it}$  than others.

At the other extreme, we assume the fully heterogenous estimation:

$$y_{it} = \alpha_i + x_{it}'\beta + u_{it}, \quad \mathbb{E}[u_{it}x_{it}] = 0, \quad \mathbb{V}[u_{it}|x_{it}] = \sigma_i^2.$$

Under  $T = 1$ , we run  $y_i = \beta_0 + x_i'\beta + v_i$ , where  $v_i = u_i + \underbrace{\alpha_i - \beta_0}_{\tilde{\alpha}_i}$  and  $\mathbb{E}[v_i] = 0$ .

Under  $T > 1$ , we run:

$$\begin{aligned} y_i &= x'_i \beta + \sum_{j=1}^n \alpha_j \mathbf{1}\{i = j\} + u_{it} \\ &= \tilde{x}'_{it} \tilde{\beta} + u_{it} \\ \tilde{x}_{it} &= \begin{bmatrix} x_{it} \\ \mathbf{1}\{i = 1\} \\ \mathbf{1}\{i = 2\} \\ \vdots \\ \mathbf{1}\{i = n\} \end{bmatrix}, \quad \tilde{\beta} = \begin{bmatrix} \beta \\ \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} \end{aligned}$$

In a similar way, we can write the regression as

$$y_i = \tilde{X}_i \tilde{\beta}_i + u_i$$

with  $\tilde{\beta}_i$  is specific for each  $i$ . We have  $n$  separate time series regressions, one for each unit  $i$ .

Following the same analyzing process, we can get:

$$\hat{\beta}_{i,OLS} = \left( \sum_i \tilde{X}_i' \tilde{X}_i \right) \sum_i \tilde{X}_i' y_i = \left( \sum_t \tilde{x}_{it} \tilde{x}_{it}' \right)^{-1} \left( \sum_t \tilde{x}_{it} y_{it} \right),$$

which obviously shows that  $\hat{\beta}$  is consistent  $\Leftrightarrow T \rightarrow \infty$ .

### 3.1.3 One-way error component model

With the fully homogeneous specification unattractive and the fully heterogeneous specification infeasible, researchers usually go for a compromise and let intercepts (and error term variances) be unit-specific.

**Definition 3.1.1** (One-way error component model).

$$y_{it} = \alpha_i + x'_{it} \beta + u_{it}, \quad \mathbb{E}[u_{it} x_{it}] = 0, \quad \mathbb{V}[u_{it} | x_{it}] = \sigma^2, \quad (3.1)$$

where  $\alpha_i$  is an individual-specific effect, and  $u_{it}$  are idiosyncratic(i.i.d.) errors.

In any case, the equation above makes clear that  $\alpha_i$  contains all factors that affect  $y_{it}$ , that are not included in  $x_{it}$  and that are fixed over time (the time-varying factors are in  $u_{it}$ ).

Suppose the model is correctly specified, and we have a cross-sectional dataset available, i.e.  $T = 1$ . Then, we would estimate:

$$y_{it} = \beta_0 + x'_{it} \beta + v_i, \quad \text{for } t = 1,$$

where  $v_i = \alpha_i + u_{it} - \beta_0$ .

If the unobserved heterogeneity  $\alpha_i$  is correlated with the covariate  $x_{it}$ , our standard OLS estimator is biased and inconsistent.

If we have a panel dataset, i.e.  $T > 1$ , we can write the above model into a regression of  $k + n$  regressors:

$$y_{it} = x'_{it} \beta + \sum_{j=1}^n \mathbf{1}\{i = j\} \alpha_j + u_{it} = x_{it}^* \beta^* + u_{it},$$

where  $x_{it}^* = (x'_{it}, \mathbf{1}\{i = 1\}, \dots, \mathbf{1}\{i = n\})'$ , and  $\beta^* = (\beta', \alpha_1, \dots, \alpha_n)'$ .

This leads to the pooled OLS estimator for  $\beta^*$ :

$$\hat{\beta}^* = \left( \sum_i \sum_t x_{it}^* x_{it}^{*'} \right) \sum_i \sum_t x_{it}^* y_{it}.$$

However, the estimator suffers from the so-called **IPP problem**, as the number of parameters increase with  $n \rightarrow \infty$ , the limit of  $\frac{1}{n} \sum_i x_{it}^* x_{it}^{*'}$  is not well-defined and as a result, we can't establish consistency of  $\hat{\beta}_{OLS}$ .

## 3.2 Random Effects

As with pooled OLS, a random effects analysis puts  $\alpha_i$  into the error term. In fact, random effects analysis imposes more assumptions than those needed for pooled OLS: **strict exogeneity** in addition to orthogonality between  $\alpha_i$  and  $x_{it}$ .

### 3.2.1 Basic Assumptions and POLS

Stating the assumption in terms of conditional means, we have:

**Assumption 3.2.1** (Random Effect).

(a)  $\mathbb{E}[u_{it}|X_i, \alpha_i] = 0, \forall t.$

(b)  $\mathbb{E}[\alpha_i|X_i] = \mathbb{E}[\alpha_i] = 0.$

where  $X_i = (x_{i1}, \dots, x_{iT})$ .

Assumption 3.2.1(a) is the strict exogeneity condition and Assumption 3.2.1(b) is how we will state the orthogonality.

**Remark** (Why Strict Exogeneity?[3]).

Why do we maintain Assumption 3.2.1(a) when it is more restrictive than needed for a pooled OLS analysis? Because the random effects approach exploits the serial correlation in the composite error,  $v_{it} = \alpha_i + u_{it}$ , in a generalized least squares (GLS) framework. In order to ensure that feasible GLS is consistent, we need some form of strict exogeneity between the explanatory variables and the composite error.

Under this assumption, we can write:

$$\begin{aligned} y_{it} &= x_{it}'\beta + v_{it} \\ \mathbb{E}[v_{it}|X_i] &= 0, t = 1, \dots, T \end{aligned}$$

The conditions shows that our model satisfies the GLS assumption, which confirms that we can apply GLS methods that account for the particular error structure  $v_{it} = \alpha_i + u_{it}$ .

By defining  $v_{it} = u_{it} + \alpha_i - \beta_0$ , we can transform the random effect model to the following:

$$\begin{aligned} y_{it} &= \alpha_i + x_{it}'\beta + u_{it} \\ &= \underbrace{\beta_0 + x_{it}'\beta}_{\tilde{x}_{it}'} + \underbrace{u_{it} + \alpha_i - \beta_0}_{\equiv v_{it}} \end{aligned}$$

Defining again  $\tilde{x}_{it} = (1, x'_{it})'$ ,  $\tilde{\beta} = (\beta_0, \beta')'$ , we can rewrite the model as:

$$\begin{aligned} y_{it} &= \tilde{x}'_{it}\beta + v_{it} \Leftrightarrow y_i = \tilde{X}'_i\tilde{\beta} + v_i \\ \rightarrow \hat{\tilde{\beta}} &= \left( \sum_i \tilde{X}'_i\tilde{X}_i \right)^{-1} \sum_i \tilde{X}'_iy_i \end{aligned}$$

With this intercept  $\beta_0$ ,  $\mathbb{E}[v_i] = 0$  is guaranteed to hold. Define  $\tilde{\alpha}_i = \alpha_i - \beta_0$  as the mean-zero unit-specific heterogeneity so that  $v_i = u_i + \tilde{\alpha}_i$ .

#### Note (POLS).

Homogenous spec:  $y_{it} = \alpha + x'_{it}\beta + u_{it} = \tilde{x}'_{it}\tilde{\beta} + v_{it}$ .  $\hat{\tilde{\beta}}$  is consistent if  $\mathbb{E}[v_{it}x_{it}] = 0, \forall t$ .

Using pooled OLS to estimate  $\hat{\tilde{\beta}}$ ,

$$\begin{aligned} \hat{\tilde{\beta}}_{RE-OLS/POLS} &= \left( \frac{1}{n} \sum_i \tilde{X}'_i\tilde{X}_i \right)^{-1} \frac{1}{n} \sum_i \tilde{X}'_iy_i \\ &= \tilde{\beta} + \left( \frac{1}{n} \sum_i \tilde{X}'_i\tilde{X}_i \right)^{-1} \frac{1}{n} \sum_i \tilde{X}'_iv_i \\ &\xrightarrow{p} \tilde{\beta} + \mathbb{E}[\tilde{X}'_i\tilde{X}_i]^{-1} \mathbb{E}[\tilde{X}'_iv_i] \\ \text{where } \mathbb{E}[\tilde{X}'_iv_i] &= \mathbb{E} \left[ \sum_t \tilde{x}'_{it}v_{it} \right] \\ &= \sum_t \mathbb{E}[\tilde{x}'_{it}v_{it}] \\ &= \sum_t \mathbb{E}[\tilde{x}_{it}(u_{it} + \alpha_i - \beta_0)] \end{aligned}$$

Here, the error term  $v_i$  is not equal to the original error term  $u_{it}$ .

#### Note.

Under the random effect, you have to use the heteroskedasticity-robust methods. Because even if we assume  $u_{it}$  to be homoskedastic,  $v_{it}$  is not, as it includes also the unit-specific heterogeneity  $\alpha_i$ .

### 3.2.2 From POLS to GLS

So, to obtain consistency, we need to assume that:

- $\mathbb{E}[u_{it}|\tilde{x}_{it}, \tilde{\alpha}_i] = 0, \forall t$ .
- $\mathbb{E}[\tilde{\alpha}_i|\tilde{x}_{it}] = 0, \forall t$ .

And, we are also obliged to use HAC-robust standard error because:

$$\Omega \equiv \mathbb{E}[v_iv'_i|\tilde{X}_i] = \mathbb{E}[(\alpha_i\mathbf{1}_i + u_i)(\tilde{\alpha}_i\mathbf{1}_i + u_i)'|\tilde{X}_i] = \mathbb{E}[\tilde{\alpha}_i^2\mathbf{1}_i\mathbf{1}'_i|\tilde{X}_i] + \mathbb{E}[u_iu'_i|\tilde{X}_i]$$

is not diagonal.

#### Assumption 3.2.2 (Random Effect).

$$\text{rank } \mathbb{E}[X'_i\Omega^{-1}X_i] = K$$



We know that both GLS and feasible GLS estimator would be consistent under Assumption 3.2.1 and 3.2.2. A general FGLS analysis, using an unrestricted variance estimator  $\Omega$ , is consistent and asymptotically normal as  $N \rightarrow \infty$ .

But, we won't exploit the unobserved effects structure  $v_{it}$ . A standard random effects analysis adds assumptions on the idiosyncratic errors that give  $\Omega$  a special form. The first assumption is that the idiosyncratic errors  $u_{it}$  have a constant unconditional variance across  $t$ :

**Assumption 3.2.3 (RE-Homoskedasticity).**

$$\mathbb{E}[u_{it}^2] = \sigma_u^2, \forall t$$

The second assumption is that the idiosyncratic errors are serially uncorrelated:

**Assumption 3.2.4 (RE-Serial Uncorrelated).**

$$\mathbb{E}[u_{it}u_{is}] = 0, \forall t \neq s$$

Under these two assumptions, we can derive the variances and covariances of the elements of  $v_i$ . Given the error structure the natural estimator for  $\beta$  is GLS. The GLS estimator for  $\beta$  is:

$$\hat{\beta}_{RE-GLS} = \left( \sum_i \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right)^{-1} \sum_i \tilde{X}_i' \Omega^{-1} y_i$$

where  $\Omega^{-\frac{1}{2}} y_i = \Omega^{-\frac{1}{2}} \tilde{X}_i' \beta + \Omega^{-\frac{1}{2}} v_i$ .

$$\begin{aligned} \Omega &= \mathbb{E}[v_i v_i' | \tilde{X}_i] = \mathbb{E} \left[ \begin{bmatrix} v_{i1} \\ v_{i2} \\ \vdots \\ v_{iT} \end{bmatrix} \begin{bmatrix} v_{i1} & v_{i2} & \cdots & v_{iT} \end{bmatrix} | \tilde{X}_i \right] \\ &= \mathbb{E} \begin{bmatrix} \mathbb{E}[v_{i1}^2 | \tilde{X}_i] & \mathbb{E}[v_{i1}v_{i2} | \tilde{X}_i] & \cdots & \mathbb{E}[v_{i1}v_{iT} | \tilde{X}_i] \\ \mathbb{E}[v_{i2}v_{i1} | \tilde{X}_i] & \mathbb{E}[v_{i2}^2 | \tilde{X}_i] & \cdots & \mathbb{E}[v_{i2}v_{iT} | \tilde{X}_i] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{E}[v_{iT}v_{i1} | \tilde{X}_i] & \mathbb{E}[v_{iT}v_{i2} | \tilde{X}_i] & \cdots & \mathbb{E}[v_{iT}^2 | \tilde{X}_i] \end{bmatrix} \\ &= \begin{bmatrix} \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i1}^2 | \tilde{X}_i] & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i1}u_{i2} | \tilde{X}_i] & \cdots & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i1}u_{iT} | \tilde{X}_i] \\ \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i2}u_{i1} | \tilde{X}_i] & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i2}^2 | \tilde{X}_i] & \cdots & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{i2}u_{iT} | \tilde{X}_i] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{iT}u_{i1} | \tilde{X}_i] & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{iT}u_{i2} | \tilde{X}_i] & \cdots & \mathbb{E}[\alpha_i^2 | \tilde{X}_i] + \mathbb{E}[u_{iT}^2 | \tilde{X}_i] \end{bmatrix} \\ &= \begin{bmatrix} \sigma_u^2 + \sigma_\alpha^2 & \sigma_\alpha^2 & \cdots & \sigma_\alpha^2 \\ \sigma_\alpha^2 & \sigma_u^2 + \sigma_\alpha^2 & \cdots & \sigma_\alpha^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_\alpha^2 & \sigma_\alpha^2 & \cdots & \sigma_u^2 + \sigma_\alpha^2 \end{bmatrix} \\ &= \sigma_\alpha^2 \mathbf{1}_i \mathbf{1}_i' + \sigma_u^2 I \\ &\text{because } \mathbb{V}[\tilde{\alpha}_i | \tilde{X}_i] = \sigma_{\alpha_i}^2 = \sigma_\alpha^2 \\ &\mathbb{V}[u_{it} | \tilde{X}_i] = \sigma_u^2, \forall i. \end{aligned}$$

where  $I$  is an identity matrix of dimension  $T_i$ . Under the assumption  $\mathbb{E}[u_{it}u_{is}] = 0$ , we now describe some statistical properties of  $\hat{\beta}_{RE-GLS}$ .

**RE Consistency**

$$\begin{aligned}
\hat{\beta}_{RE-GLS} - \tilde{\beta} &= \left( \sum_i \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right)^{-1} \left( \sum_i \tilde{X}_i' \Omega^{-1} v_i \right) \\
&\rightarrow \mathbb{E} \left[ \sum_i \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right] \mathbb{E} \left[ \sum_i \tilde{X}_i' \Omega^{-1} v_i \right] \\
\text{where } \mathbb{E} \left[ \sum_i \tilde{X}_i' \Omega^{-1} v_i \right] &= \sum_i \mathbb{E} \left[ \tilde{X}_i' \Omega^{-1} v_i \right] \\
&= \sum_i \tilde{X}_i' \Omega^{-1} \mathbb{E}[v_i | \tilde{X}_i] \\
&= \sum_i \tilde{X}_i' \Omega^{-1} \mathbb{E}[u_i + \tilde{\alpha}_i | \tilde{X}_i] \\
&= 0
\end{aligned}$$

Thus,  $\hat{\beta}_{RE-GLS}$  is conditionally unbiased for  $\tilde{\beta}$ . The conditional variance of  $\hat{\beta}_{RE-GLS}$  is:

$$\mathbb{V}[\hat{\beta}_{RE-GLS}] = \left( \sum_i \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right)^{-1} \sigma_u^2$$

**RE Asymptotic Distribution**

The asymptotic variance of  $\hat{\beta}_{RE-GLS}$  is:

$$\begin{aligned}
\sqrt{n} \left( \hat{\beta}_{RE-GLS} - \tilde{\beta} \right) &\xrightarrow{d} \mathcal{N}(0, V) \\
\text{where } V_{GLS} &= \mathbb{E} \left[ \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right]^{-1} \mathbb{E} \left[ \tilde{X}_i' \Omega^{-1} v_i v_i' \Omega^{-1} \tilde{X}_i \right] \mathbb{E} \left[ \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right] \\
&= \mathbb{E} \left[ \tilde{X}_i' \Omega^{-1} \tilde{X}_i \right]^{-1} \underbrace{\mathbb{E}[v_i v_i' | \tilde{X}_i]}_{\equiv \Omega}
\end{aligned}$$

Because we do not know  $\Omega$ , the RE-GLS estimator is infeasible.

If indeed we have:

$$\begin{aligned}
\Omega &= \mathbb{E}[v_i v_i' | \tilde{X}_i] \\
&= \mathbb{E}[(\alpha_i \mathbf{1}_i + u_i)(\alpha_i \mathbf{1}_i + u_i)' | \tilde{X}_i] \\
&= \mathbb{E}[\alpha_i^2] \mathbf{1}_i \mathbf{1}_i' + \mathbb{E}[u_i u_i' | \tilde{X}_i]
\end{aligned}$$

which implies homoskedasticity.

A feasible version replaces  $\Omega$  with an estimator  $\hat{\Omega}_i$ . Assuming homoskedasticity of the original errors:

$$\begin{aligned}
\mathbb{E}[u_i u_i' | \tilde{X}_i, \tilde{\alpha}_i] &= \sigma_u^2 I_T \\
\mathbb{E}[\tilde{\alpha}_i^2 | \tilde{x}_i] &= \sigma_\alpha^2
\end{aligned}$$

We obtain:  $\hat{\Omega} = \hat{\sigma}_\alpha^2 \mathbf{1}_i \mathbf{1}_i' + \hat{\sigma}_u^2 I_T$ , a  $T \times T$  matrix that we assume to be positive definite. In a panel data context, the FGLS estimator that uses this variance matrix is what is known as the **random effects estimator**.

Hence, the motivation for using GLS is different than under a cross-sectional regression with heteroskedasticity. We use GLS because of the autocorrelation in  $v_{it}$  induced by the presence of time variant  $\alpha_i$ .

### 3.2.3 Comparing POLS and GLS

Now, let's compare the  $\hat{\beta}_{RE-GLS}$  with the pooled estimator  $\hat{\beta}_{POLS}$ .

Under the assumptions of the random effects model, POLS estimator is also unbiased for  $\beta$  and has conditional variance:

$$V_{POLS} = \left( \sum_i X_i' X_i \right)^{-1} \left( X_i' \Omega_i X_i \right)^{-1} \left( X_i' X_i \right)^{-1}$$

Using the algebra of the Gauss-Markov Theorem we deduce that:

$$V_{RE-GLS} \leq V_{POLS}$$

and thus the random effects estimator  $\hat{\beta}_{RE-GLS}$  is more efficient than  $\hat{\beta}_{POLS}$  under the strict exogeneity assumption 3.2.1. The two variance matrices are identical when there is no individual-specific effect  $\sigma_\alpha^2 = 0$  for then  $V_{RE-GLS} = V_{POLS} = (X'X)^{-1} \sigma_u^2$ .

Under the assumption that the random effects model is a useful approximation but not literally true, we may use the cluster-robust covariance matrix estimator such as:

$$\hat{V}_{RE-GLS} = \left( \sum_i X_i' \Omega_i X_i \right)^{-1} \left( \sum_i X_i' \Omega_i \hat{v}_i \hat{v}_i' \Omega_i' X_i \right)^{-1} \left( \sum_i X_i' \Omega_i X_i \right)^{-1}$$

where  $\hat{v}_i = y_i - X_i \hat{\beta}_{RE-GLS}$ , This may be re-scaled by a degree of freedom adjustment if desired.

## 3.3 Fixed Effects

In the econometrics literature if the stochastic structure of  $\alpha_i$  is treated as unknown and possibly correlated with  $x_{it}$ , then  $\alpha_i$  is called a **fixed effect**.

Correlation between  $\alpha_i$  and  $x_{it}$  will cause both pooled and random effect estimators to be biased.

We transform equation to get rid of  $\alpha_i$ :  $y_{it} = \alpha_i + x_{it}'\beta + u_{it}$ . This is due to the classic problems of omitted variables bias and endogeneity.

The presence of the unstructured individual effect  $\alpha_i$  means that it is not possible to identify  $\beta$  under a simple projection assumption such as  $\mathbb{E}[u_{it}x_{it}] = 0$ . It turns out that a sufficient condition for identification is the following.

**Definition 3.3.1** (Strictly exogeneity).

A regressor  $x_{it}$  is said to be strictly exogeneity if  $\mathbb{E}[x_{it}u_{is}] = 0, \forall t, s = 1, \dots, T$ .

Strict exogeneity is a strong projection condition, meaning that if a  $X_{is}, s \neq t$  is added into the regression model, it would have a zero coefficient. Strict exogeneity is a projection analog of the **strict mean independence**:

$$\mathbb{E}[u_{it}|X_i] = 0$$

which implies the strict exogeneity but not vice versa.

The strict exogeneity assumption 3.3.1 is sufficient for identification and asymptotic theory, we'll also use the strict mean independence assumption for finite sample analysis.

**Remark** (About strict exogeneity[2]).

Strict exogeneity (assumption 3.3.1) is typically inappropriate in dynamic models.

### 3.3.1 Within Transformation

In previous steps, we showed that if  $x_{it}$  and  $\alpha_i$  are correlated, then pooled OLS and RE-GLS estimator would be biased and inconsistent. If we leave the relationship between  $\alpha_i$  and  $x_{it}$  fully unstructured, then the only way to consistently estimate the coefficient  $\beta$  is by an estimator which is invariant to  $\alpha_i$ .

The first fixed effects (FE) assumption is strict exogeneity of the explanatory variables conditional on  $\alpha_i$ :

**Assumption 3.3.1** (FE Strict Exogeneity).

$$\mathbb{E}[u_{it}|X_i, \alpha_i] = 0, \forall t = 1, \dots, T$$

This assumption is identical to the assumption 3.2.1(a), we maintain strict exogeneity of  $x_{it}, t = 1, \dots, T$  conditional on the unobserved effect. The key difference is that *we do not assume assumption 3.2.1(b), which means that, for FE analysis,  $\mathbb{E}[\alpha_i|X_i]$  can be any function of  $X_i$ .*

By relaxing assumption 3.2.1(b), we can consistently estimate partial effects in the presence of time-consistent omitted variables that can be arbitrarily related to unobserved variables  $x_{it}$ . *Therefore, FE analysis is more robust than RE analysis.*

But this robustness has a cost: we can not include any time-constant variables in  $x_{it}$  without further assumptions. The reason is simple: if  $\alpha_i$  can be arbitrarily correlated with each element of  $x_{it}$ , then there's no way to distinguish the effect of time-constant observables from the time-constant unobservable  $\alpha_i$ .

The first transformation is the **within transformation**. Define the mean of a variable for a given individual as

$$\begin{aligned}\bar{y}_i &= \frac{1}{T} \sum_t y_{it} \\ \bar{x}_i &= \frac{1}{T} \sum_t x_{it} \\ \bar{u}_i &= \frac{1}{T} \sum_t u_{it}\end{aligned}$$

We call this the **individual-specific mean** since it is the mean of a given individual. <sup>1</sup>

Then, subtracting the individual-specific mean from the variable we obtain the deviations:

$$\begin{aligned}(y_{it} - \bar{y}_i) &= (x_{it} - \bar{x}_i)' \beta + (u_{it} - \bar{u}_i) + (\alpha_i - \alpha_i) \\ \dot{y}_{it} &= \dot{x}_{it}' \beta + \dot{u}_{it} \\ \ddot{y}_i &= \ddot{X}_i' \beta + \ddot{u}_i\end{aligned}$$

This is the **within transformation**. We also refer to  $\ddot{y}_{it}$  as the **demeaned values** or **deviation from individual means**. *What is important is that the demeaning has occurred at the individual level.*

Denote the time-averages method by  $\hat{\beta}_{FE-W}$ , in order to ensure that the FE estimator is consistent and well behaved asymptotically, we need a standard rank condition on the matrix of time-demeaned explanatory variables:

**Assumption 3.3.2** (FE full rank).

$$\text{rank} \sum_t \mathbb{E}[\dot{x}_{it}' \dot{x}_{it}] = \text{rank} \mathbb{E}[\ddot{X}_i' \ddot{X}_i] = K$$

<sup>1</sup>Some authors call this the **time-average** or **time-mean** since it is the average over the time periods.

### FE Consistency

$$\begin{aligned}
\hat{\beta}_{FE-W} &= \left( \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1} \left( \ddot{X}_i' \ddot{y}_i \right) \\
&= \left( \sum_i \sum_t \ddot{x}_{it} \ddot{x}_{it}' \right)^{-1} \sum_i \sum_t \ddot{x}_{it} \ddot{y}_{it} \\
&= \beta + \left( \sum_i \sum_t \ddot{x}_{it} \ddot{x}_{it}' \right)^{-1} \sum_i \sum_t \ddot{x}_{it} \ddot{u}_{it} \\
&\xrightarrow{p} \beta + \mathbb{E} \left[ \sum_t \ddot{x}_{it} \ddot{x}_{it}' \right]^{-1} \mathbb{E} \left[ \sum_t \ddot{x}_{it} \ddot{u}_{it} \right]
\end{aligned}$$

where  $\mathbb{E} \left[ \sum_t \ddot{x}_{it} \ddot{u}_{it} \right] = \sum_t \mathbb{E} [\ddot{x}_{it} \ddot{u}_{it}]$

$$\begin{aligned}
\mathbb{E} [\ddot{x}_{it} \ddot{u}_{it}] &= \mathbb{E} \left[ \left( x_{it} - \frac{1}{T} \sum_t x_{it} \right) \left( u_{it} - \frac{1}{T} \sum_t u_{it} \right)' \right] \\
&= 0 \quad \text{if } u_{it} \perp\!\!\!\perp x_{is}, \forall t, s = 1, \dots, T.
\end{aligned}$$

Then, let  $\Sigma_i = \mathbb{E}[u_i u_i' | X_i]$  denote the  $T_i \times T_i$  covariance matrix of the idiosyncratic errors. The variance of  $\hat{\beta}_{FE-W}$  is:

$$V_{FE-W} = \mathbb{V}[\hat{\beta}_{FE-W} | X_i] = \left( \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1} \left( \sum_i \ddot{X}_i' \Sigma_i \ddot{X}_i \right)^{-1} \left( \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1}$$

This expression simplifies when the idiosyncratic errors are homoskedastic and serially uncorrelated:

**Assumption 3.3.3** (FE homoskedasticity).

- (a)  $\mathbb{E}[u_{it}^2 | X_i] = \sigma_u^2$
- (b)  $\mathbb{E}[u_{it} u_{is} | X_i] = 0, \forall s \neq t.$

### FE Asymptotic Distribution

In this case,  $\Sigma_i = \sigma_u^2 I_i$  and  $V_{FE-W}$  simplifies to:

$$V_{FE-W}^0 = \sigma_u^2 \left( \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1}$$

We can also write the asymptotic distribution as below

$$\begin{aligned}
\sqrt{n}(\hat{\beta}_{FE-W} - \beta) &= \left( \frac{1}{N} \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1} \left( N^{-\frac{1}{2}} \sum_i \ddot{X}_i' \ddot{u}_i \right) \\
&= \left( \frac{1}{N} \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1} \left( N^{-\frac{1}{2}} \sum_i \ddot{X}_i' u_i \right)^2 \\
&\rightarrow \mathbb{E}[\ddot{X}_i' \ddot{X}_i]^{-1} \cdot \mathcal{N}(0, \mathbb{V}[\ddot{X}_i' \ddot{u}_i]) \\
&\sim \mathcal{N}(0, V_{FE-W})
\end{aligned}$$

where  $V_{FE-W} = \sigma_u^2 \mathbb{E}[\ddot{X}_i' \ddot{X}_i]^{-1}$

**Remark (FE VS. POLS).**

It is instructive to compare the variances of the fixed-effects and pooled estimators under

$$\begin{aligned}\mathbb{E}[u_{it}^2|X_i] &= \sigma_u^2 \\ \mathbb{E}[u_{it}u_{is}|X_i] &= 0, \forall s \neq t.\end{aligned}$$

and the assumption that there is no individual-specific effect,  $\alpha_i = 0$ . In this case, we can see that:

$$V_{FE-W}^0 = \sigma_u^2 \left( \sum_i \ddot{X}_i' \ddot{X}_i \right)^{-1} \geq \sigma_u^2 \left( \sum_i X_i' X_i \right)^{-1} = V_{POLS}.$$

The inequality holds since the demeaned variables  $\ddot{X}_i$  have reduced variation compared to the original observations  $X_i$ .

This shows the cost of using fixed effects relative to pooled estimation. The estimation variance increases due to reduced variation in the regressors. This reduction in efficiency is a necessary by-product of the robustness of the estimator to the individual effects  $\alpha_i$ .

**3.3.2 First Difference Transformation**

Another important transformation which does the same as within transformation is **first-differencing**. *This can be applied to all but the first observation (which is essentially lost).*

$$\begin{aligned}y_{it} - y_{i,t-1} &= (x_{it} - x_{i,t-1})'\beta + (u_{it} - u_{i,t-1}) \\ \Delta y_{it} &= \Delta x_{it}'\beta + \Delta u_{it}, i = 1 \cdots n, t = 2 \cdots T \\ \Delta y_i &= \Delta X_i\beta + \Delta u_i\end{aligned}$$

We can see that the individual effect  $\alpha_i$  has been eliminated.

Denote the first difference method by  $\hat{\beta}_{FE-FD}$ , the fixed effect estimator is consistent and asymptotically normal based on two assumptions.

**Assumption 3.3.4 (FD Strict exogeneity).**

It's the same as FE's assumption 3.3.1.

**Assumption 3.3.5 (FD Full rank).**

$$\text{rank} \sum_{t=2}^T \mathbb{E}[\Delta x_{it}' \Delta x_{it}] = K$$

<sup>2</sup>From the regression model  $\ddot{y}_i = \ddot{X}_i\beta + \ddot{u}_i$ , where  $\ddot{y}_i$  is  $T \times 1$ ,  $\ddot{X}_i$  is  $T \times K$ , and  $\ddot{u}_i$  is  $T \times 1$ . We can write the individual-specific mean as  $\bar{y}_i = (\mathbf{1}_i' \mathbf{1}_i)^{-1} \mathbf{1}_i' y_i$ . Then, we can define a **individual-specific demeaning operator**:

$$M_i = I_i - \mathbf{1}_i(\mathbf{1}_i' \mathbf{1}_i)^{-1} \mathbf{1}_i',$$

giving that

$$\ddot{y}_i = y_i - \mathbf{1}_i \bar{y}_i = y_i - \mathbf{1}_i(\mathbf{1}_i' \mathbf{1}_i)^{-1} \mathbf{1}_i' y_i = M_i y_i.$$

Notice that  $M_i$  is idempotent ( $M_i M_i = M_i$ ,  $N_i' = M_i$ ). Similarly for  $\ddot{X}_i$  and  $\ddot{u}_i$ .

Thus, we have:

$$\ddot{X}_i' \ddot{u}_i = X_i' M_i M_i u_i = X_i' M_i u_i = \ddot{X}_i' u_i.$$

**FE-FD Consistency**

$$\begin{aligned}
\hat{\beta}_{FE-FD} &= \left( \sum_i \sum_t \Delta x_{it} \Delta x'_{it} \right)^{-1} \sum_i \sum_t \Delta x_{it} \Delta y_{it} \\
&= \beta + \left( \frac{1}{n} \sum_i \sum_t \Delta x_{it} \Delta x'_{it} \right)^{-1} \frac{1}{n} \sum_i \sum_t \Delta x_{it} \Delta u_{it} \\
&\xrightarrow{p} \beta + \mathbb{E} \left[ \sum_t \Delta x_{it} \Delta x'_{it} \right]^{-1} \mathbb{E} \left[ \sum_t \Delta x_{it} \Delta u_{it} \right] \\
\text{where } \mathbb{E} \left[ \sum_t \Delta x_{it} \Delta u_{it} \right] &= \sum_t \mathbb{E} [\Delta x_{it} \Delta u_{it}] \\
\mathbb{E} [\Delta x_{it} \Delta u_{it}] &= \mathbb{E} [(x_{it} - x_{i,t-1})(u_{it} - u_{i,t-1})'] \\
&= 0 \quad \text{if } x_{it} \perp\!\!\!\perp (u_{it}, u_{i,t-1}), \forall t.
\end{aligned}$$

For  $T = 2$ ,  $\hat{\beta}_{FE-FD} = \hat{\beta}_{FE-W}$ , equals the fixed effects estimator and they differ however, for  $T > 2$  (See Hanse, 2022[2]).

**FE-FD Asymptotic Distribution**

We just use the standard calculation:

$$\sqrt{n}(\hat{\beta}_{FE-FD} - \beta) \xrightarrow{d} \mathcal{N}(0, V_{FE-FD})$$

where

$$V_{FE-FD} = \mathbf{E} \left[ \sum_{t=2}^T \Delta x_{it} \Delta x'_{it} \right]^{-1} \mathbf{E} \left[ \left( \sum_{t=2}^T \Delta x_{it} \Delta u_{it} \right) \left( \sum_{s=2}^T \Delta x_{is} \Delta u_{is} \right)' \right] \mathbf{E} \left[ \sum_{t=2}^T \Delta x_{it} \Delta x'_{it} \right]^{-1}$$

If we still assume that the first-difference error term  $\Delta u_{it}$  is homoskedastic:

**Assumption 3.3.6** (FD homoskedasticity).

Denote  $e_{it} \equiv \Delta u_{it}$ ,  $e_i$  is the stack of  $e_{it}$  for  $t = 2, \dots, T$ .  $\mathbb{E}[e_i e_i' | X_i, \alpha_i] = \sigma_e^2 I$

then, we can write:

$$AV[\hat{\beta}_{FE-FD}] = \hat{\sigma}_e^2 \left( \sum_i \Delta X_i' \Delta X_i \right)^{-1}$$

where  $\hat{\sigma}_e^2$  is a consistent estimator of  $\sigma_e^2$ , and the simplest estimator is obtained by computing the OLS residuals:

$$\hat{e}_{it} = \Delta y_{it} - \Delta x_{it} \hat{\beta}_{FE-FD}$$

from the pooled regression.

If the assumption 3.3.6 is violated, replacing expectations with sample means and  $\Delta u_{it}(e_{it})$  with  $\widehat{\Delta u_{it}}(\hat{e}_{it})$  yields the HAC-robust variance estimator  $\hat{V}_{FE-FD}$ .

$$\hat{V}_{FE-FD} = \left( \sum_i \Delta X_i' \Delta X_i \right)^{-1} \left( \sum_i \Delta X_i' \hat{e}_{it} \hat{e}_{it}' \Delta X_i \right) \left( \sum_i \Delta X_i' \Delta X_i \right)^{-1}$$

**Remark** (About FE-W and FE-FD (Hansen, 2022 [2])).

The FD method is not as strong as the within method, because it only requires that the variable is uncorrelated with the error term in the same period and the previous period.

If there is a correlation between the error term in current period and two periods ago, there is a problem of feedback loop, which we will imply the correlated random effect model.

### 3.3.3 Hausman Test for Random vs. Fixed Effects

Even if strict exogeneity is satisfied, the consistency of FE estimators comes at an efficiency loss compared to the RE-GLS and POLS estimators. This is easiest seen in the FD-transformation, in which we lose the  $n$  observations pertaining to the first time period  $t = 1$ .

The efficiency loss of the Within-estimator is somewhat more subtle. It arises because the Within-estimator only exploits variation across time and disregards the time-constant variation across cross-sectional units.

As a result, if the core RE assumption of  $X_i$  and  $\alpha_i$  being uncorrelated is indeed satisfied, we prefer the RE-estimators. If instead it is violated, we of course prefer the less efficient but consistent FE estimators.

**Theorem 3.3.1 (Hausman-Test).**

$$\mathcal{H}_0: \hat{\beta}_{RE-GLS} - \hat{\beta}_{FE-W} = 0$$

We define:

$$T_{Hausman} = n(\hat{\beta}_{FE} - \hat{\beta}_{RE})' \left( A\mathbb{V}[\hat{\beta}_{FE}] - A\mathbb{V}[\hat{\beta}_{RE}] \right)^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE}) \rightarrow \chi_k^2$$

If  $\mathcal{H}_0$  is accepted, the difference between  $\hat{\beta}_{RE-GLS}$  and  $\hat{\beta}_{FE-W}$  is small enough to suggest that both estimators are consistent. that  $X_i$  and  $\alpha_i$  are indeed uncorrelated, and therefore, we should use the more efficient estimator  $\hat{\beta}_{RE-GLS}$ .

If the test rejects this is evidence that the individual effect  $u_i$  is correlated with the regressors so the random effects model is not appropriate.

**Note.**

To sum up, the FE estimators work under arbitrary correlation between the unobserved heterogeneity  $\alpha_i$  and covariates  $X_i$ , but they cannot deal with time-constant regressors and their consistency is paid for by an efficiency loss relative to RE estimators.

Most importantly, their consistency requires strict exogeneity, a much stronger assumption than contemporaneous exogeneity of covariates and error terms.

**Remark** (Random Effects or Fixed Effects?(Hansen, 2022[2])).

We have presented the random effects and fixed effects estimators of the regression coefficients. Which should be used in practice? How should we view the difference?

The basic distinction is that the random effects estimator requires the individual error  $\alpha_i$  to satisfy the conditional mean assumption  $\mathbb{E}[\alpha_i|X_i] = 0$ . The fixed effects estimator does not require this condition, and is robust to its violation.

In particular, the individual effect  $\alpha_i$  can be arbitrarily correlated to the regressors. On the other hand the random effects estimator is efficient under random effects.

Current econometric practice is to prefer robustness over efficiency. Consequently, current practice is (nearly uniformly) to use the fixed effects estimator for linear panel data models. Random effects



estimators are only used in contexts where fixed effects estimation is unknown or challenging (which occurs in many nonlinear models).

The labels “random effects” and “fixed effects” are misleading. These are labels which arose in the early literature and we are stuck with these labels today. In a previous era regressors were viewed as “fixed”. Viewing the individual effect as an unobserved regressor leads to the label of the individual effect as “fixed”. Today, we rarely refer to regressors as “fixed” when dealing with observational data. We view all variables as random. Consequently describing  $\alpha_i$  as “fixed” does not make much sense and it is hardly a contrast with the “random effect” label since under either assumption  $\alpha_i$  is treated as random. Once again, the labels are unfortunate but the key difference is whether  $\alpha_i$  is correlated with the regressors.

### 3.3.4 FE-IV Estimation

1. Contemporaneous exogeneity:  $\mathbb{E}[x_{it}u_{it}] = 0, \forall t$ .
2. Strict exogeneity:  $\mathbb{E}[x_{it}u_{is}] = 0, \forall t, s$ .
3. Sequential exogeneity:  $\mathbb{E}[x_{it}u_{is}] = 0, \forall t, s \geq t$ .

#### Definition 3.3.2 (Predetermined variables(Or Sequential Exogeneity)).

Predetermined variables are variables that were determined prior to the current period. In econometric models this implies that the current period error term is uncorrelated with current and lagged values of the predetermined variable but may be correlated with future values. This is a weaker restriction than strict exogeneity, which requires the variable to be uncorrelated with past, present, and future shocks.

The models we have discussed so far have been static with no dynamic relationships. In many economic contexts it is natural to expect that behavior and decisions are dynamic, explicitly depending on past behavior.

The workhorse dynamic model in a panel framework is the  $p$ -th order autoregression with regressors and a one-way error component structure(see 3.1.3). This is:

$$y_{it} = \alpha_1 y_{i,t-1} + \dots + \alpha_p y_{i,t-p} + x'_{it} \beta + \alpha_i + u_{it} \quad (3.2)$$

where  $\alpha_j$  are the autoregressive coefficients.  $x_{it}$  is a  $k$ -vector of regressors,  $\alpha_i$  is an individual effect and  $u_{it}$  is an idiosyncratic error. It's conventional to assume that  $u_{it}$  and  $\alpha_i$  are mutually independent and the  $u_{it}$  are serially uncorrelated and mean zero. For the present we will assume that the regressors  $x_{it}$  are strictly exogenous(assumption 3.3.1). Currently, we focus on the AR(1) model:

$$y_{it} = \alpha_i + u_{it} + \beta_1 y_{i,t-1} + x'_{it} \beta_{-1}$$

where  $\beta_{-1}$  is a  $k-1$  vector of coefficients on all other regressors.

#### Definition 3.3.3 (Anderson and Hsiao(1981)).

Anderson and Hsiao (1982) made an important breakthrough by showing that a simple instrumental variables estimator is consistent for the parameters of 3.2. he method first eliminates the individual effect  $\alpha_i$  by first differencing:

$$\begin{aligned} y_{it} &= \alpha_i + x'_{it} \beta + u_{it} \\ &= \alpha_i + \beta_1 y_{i,t-1} + \tilde{x}'_{it} \beta_{-1} + u_{it} \end{aligned}$$

$$\Rightarrow \Delta y_{it} = \beta_1 \Delta y_{i,t-1} + \Delta x'_{it} \beta + \Delta u_{it}$$

The challenge is that first-differencing induces correlation between  $\Delta y_{i,t-1}$  and  $\Delta u_{it}$ :

$$\mathbb{E}[\Delta y_{i,t-1} \Delta u_{it}] = \mathbb{E}[(y_{i,t-1} - y_{i,t-2})(u_{it} - u_{i,t-1})] = -\sigma_u^2.$$

The other regressors are not correlated with  $\Delta u_{it}$ . For  $s > 1$ ,  $\mathbb{E}[\Delta y_{i,t-s} \Delta u_{it}] = 0$  and  $x_{it}$  is strictly exogenous  $\mathbb{E}[\Delta x_{it} \Delta u_{it}] = 0$ . The correlation between  $\Delta y_{i,t-1}$  and  $\Delta u_{it}$  is endogeneity. One solution to endogeneity is to use an instrument. Anderson-Hsiao pointed out that  $y_{i,t-2}$  is a valid instrument because it is correlated with  $\Delta y_{i,t-1}$  yet uncorrelated with  $\Delta u_{it}$ . Under sequential exogeneity, instrument-exogeneity is satisfied:  $\mathbb{E}[y_{i,t-2} \Delta u_{it}] = \mathbb{E}[y_{i,t-2} \Delta u_{it}] - \mathbb{E}[y_{i,t-2} \Delta u_{i,t-1}] = 0$ .

This is the IV using the instruments  $(y_{i,t-2}, \dots, y_{i,t-s-1})$  for  $(\Delta y_{i,t-1}, \dots, \Delta y_{i,t-s})$ . The estimator requires  $T \geq s + 2$ .

$$\mathbb{E}[y_{is} \Delta u_{it}] = 0, \forall s \leq t - 2.$$

The Anderson-Hsiao estimator is IV using  $Y_{i,t-2}$  as an instrument for  $\Delta Y_{i,t-1}$ . Equivalently, this is IV using the instruments  $(Y_{i,t-2}, \dots, Y_{i,t-p-1})$  for  $(\Delta Y_{i,t-1}, \dots, \Delta Y_{i,t-p})$ . The estimator requires  $T \geq p + 2$ .

To show that this estimator is consistent, for simplicity assume we have a balanced panel with  $T = 3$ ,  $p = 1$ , and no regressors. In this case the Anderson-Hsiao IV estimator is

$$\hat{\alpha}_{iv} = \left( \sum_{i=1}^N Y_{i1} \Delta Y_{i2} \right)^{-1} \left( \sum_{i=1}^N Y_{i1} \Delta Y_{i3} \right) = \alpha + \left( \sum_{i=1}^N Y_{i1} \Delta Y_{i2} \right)^{-1} \left( \sum_{i=1}^N Y_{i1} \Delta \varepsilon_{i3} \right).$$

Under the assumption that  $\varepsilon_{it}$  is serially uncorrelated, (17.88) shows that  $\mathbb{E}[Y_{i1} \Delta \varepsilon_{i3}] = 0$ . In general,  $\mathbb{E}[Y_{i1} \Delta Y_{i2}] \neq 0$ . As  $N \rightarrow \infty$

$$\hat{\alpha}_{iv} \xrightarrow{p} \alpha - \frac{\mathbb{E}[Y_{i1} \Delta \varepsilon_{i3}]}{\mathbb{E}[Y_{i1} \Delta Y_{i2}]} = \alpha.$$

Thus the IV estimator is consistent for  $\alpha$ .

The Anderson-Hsiao IV estimator relies on two critical assumptions. First, the validity of the instrument (uncorrelatedness with the equation error) relies on the assumption that the dynamics are correctly specified so that  $\varepsilon_{it}$  is serially uncorrelated. For example, many applications use an AR(1). If instead the true model is an AR(2) then  $Y_{i,t-2}$  is not a valid instrument and the IV estimates will be biased. Second, the relevance of the instrument (correlatedness with the endogenous regressor) requires  $\mathbb{E}[Y_{i1} \Delta Y_{i2}] \neq 0$ . This turns out to be problematic and is explored further in Section 17.40. These considerations suggest that the validity and accuracy of the estimator are likely to be sensitive to these unknown features.

Figure 3.1: Anderson and Hsiao(1981)

Using similar reasoning, other approaches use sequential exogeneity to circumvent FE methods altogether rather than to save their consistency. For example, Blundell and Bond (1998) start from the original specification:

$$y_{it} = x'_{it} \beta + \alpha_i + u_{it},$$

where correlation between  $\alpha_i$  and  $x_{it}$  is suspected to be due to  $y_{i,t-1}$ , contained in  $x_{it}$ .

**Definition 3.3.4** (Blundell and Bond(1998)).

$$\begin{aligned} y_{it} &= \alpha_i + \beta_1 y_{i,t-1} + u_{it} \\ &= \beta_1 y_{i,t-1} + (u_{it} + \alpha_i) \end{aligned}$$

Use  $\Delta y_{i,t-1}$  as the IV for  $y_{i,t-1}$

## Time Series

### 4.1 Univariate Time Series

We have a sample  $\{w_i\}_{i=1}^n$ , with  $w_i = (y_i, x_i')'$ ,

$\{w_{it}\}_{i=1:n, t=1:T}$ .

Now, we look at  $\{w_t\}_{t=1}^T$ , usually written as  $y_t$ , is univariate time series data.

In the cross-sectional context, we average over  $i$  to get

$$\mathbb{E}[u_i] = \int u_i f_u(u_i) du_i.$$

Under time series data, we also think  $y_t$  as a RV. without i.i.d. assumption, we generally have  $T$  realizations of different and mutually dependent variables.

$$\begin{aligned}\mathbb{E}[y_t] &= \int y_t f_{y_t}(y_t) dy_t = \mu_t, \\ \mathbb{V}[y_t] &= \mathbb{E}[(y_t - \mu_t)^2] = \gamma_{0,t}, \\ \text{Cov}(y_t, y_{t-h}) &= \mathbb{E}[(y_t - \mu_t)(y_{t-h} - \mu_{t-h})] = \gamma_{h,t}.\end{aligned}$$

**Definition 4.1.1 (Weak Stationarity).**

$y_t$  is a weakly stationary process if

1.  $\mu_t = \mu$  for all  $t$ ,
2.  $\gamma_{h,t} = \gamma_h$  for all  $t$ .

autocovariance function (ACF):  $\{\gamma_0, \gamma_1, \dots\}$  autocorrelation function:  $\{\rho_0, \rho_1, \dots\}$ , where  $\rho_h = \frac{\gamma_h}{\gamma_0}$ .

## Appendix

## Recommended Resources

### Books

- [1] Peng Ding. *A First Course in Causal Inference*. 2023. arXiv: [2305.18793](https://arxiv.org/abs/2305.18793) [stat.ME]. URL: <https://arxiv.org/abs/2305.18793> (p. 6)
- [2] Bruce E. Hansen. *Econometrics*. Princeton, New Jersey: Princeton University Press, 2022 (pp. 9, 16, 20, 21)
- [3] Jeffrey M. Wooldridge. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, Massachusetts: The MIT Press, 2010 (p. 12)
- [4] James H. Stock and Mark W. Watson. *Introduction to Econometrics*. 4th ed. New York: Pearson, 2003
- [5] Jeffrey M. Wooldridge. *Introductory Econometrics: A Modern Approach*. 7th ed. Cengage Learning, 2020
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- [9] James D. Hamilton. *Time Series Analysis*. Princeton, New Jersey: Princeton University Press, 1994. ISBN: 9780691042893
- [10] Takeshi Amemiya. *Advanced Econometrics*. Cambridge, MA: Harvard University Press, 1985

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- [11] Donald B. Rubin. “Bayesian Inference for Causality: The Importance of Randomization”. In: *The Annals of Statistics* 3.1 (1975), pp. 121–131. DOI: [10.1214/aos/1176343238](https://doi.org/10.1214/aos/1176343238) (p. 6)
- [12] Paul W. Holland. “Statistics and Causal Inference(with discussion)”. In: *Journal of the American Statistical Association* 81.396 (1986), pp. 945–960. DOI: [10.1080/01621459.1986.10478373](https://doi.org/10.1080/01621459.1986.10478373) (p. 6)
- [13] Jerzy Neyman. “On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9”. In: *Statistical Science* 5.4 (1923), pp. 465–472 (p. 6)
- [14] Donald B. Rubin. “Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies”. In: *Journal of Educational Psychology* 66.5 (1974), pp. 688–701. DOI: [10.1037/h0037350](https://doi.org/10.1037/h0037350) (p. 6)
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